

OHBM2026 abstract

Title:

"MPRAGELike: a novel approach to generate T1w images from Multi-Contrast Gradient Echo images"

Authors & affiliation

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Introduction:

Magnetization-Prepared Rapid Acquisition of Gradient Echoes (MPRAGE) sequences provide excellent white and gray matter (WM-GM) contrast, within short acquisition time [1]. MPRAGE-images are therefore the preferred anatomical reference image in most neuroimaging studies.

Advanced neuroimaging protocols such as applied in Alzheimer's and Parkinson's Diseases research have recently been extended to include quantitative parameter mapping methods, such as Multi-Parameter Mapping (MPM) imaging. These methods acquire multi-contrast spoiled Gradient Echo (GRE) images in relatively short time for the calculation of quantitative maps (qMaps) and have become valuable tools for multi-center neuroimaging studies [2]. However, MPRAGE is usually still included due to its high importance as an anatomical reference and basis for automatic segmentation. When combining anatomical multi-contrast imaging and quantitative parameter mapping, MRI acquisition protocols can become prohibitively long, especially with patients.

Here we extend *MPRAGELike*, a novel and straightforward method to synthesize MPRAGE-like T1w images from MPM images [3], by providing a Matlab version of the tool with some extra features compared to the original Python implementation (see Methods section and "code availability" in the Conclusion section). We also present some validation results from Fortin et al. 2025 [3],

Methods:

The raw T1w MPM images do not provide sufficient morphometric details to be used for visual assessment or automatic brain segmentation. On the other hand, compared to the T1w, PDw and MTw contrasts in the MPM protocol provide an approximately "inverted" contrast. The rationale behind calculating *MPRAGELike* images is (1) to increase the T1w contrast-to-noise ratio (CNR) by dividing the T1w image by the approximately "inverted" contrast images acquired in the MPM protocol, (2) thereby reducing receive bias and residual transmit bias, and (3) cancelling out T2* bias [4], without the need to calculate qMaps. The following three equations for generating *MPRAGELike* images were tested, see Figure 1, where PDw, MTw, and T1w are the 1st TE magnitude MPM images and λ , the regularization term. Note that before estimating the (regularized) ratio of images, these should be coregistered to correct for any in-between image movement.

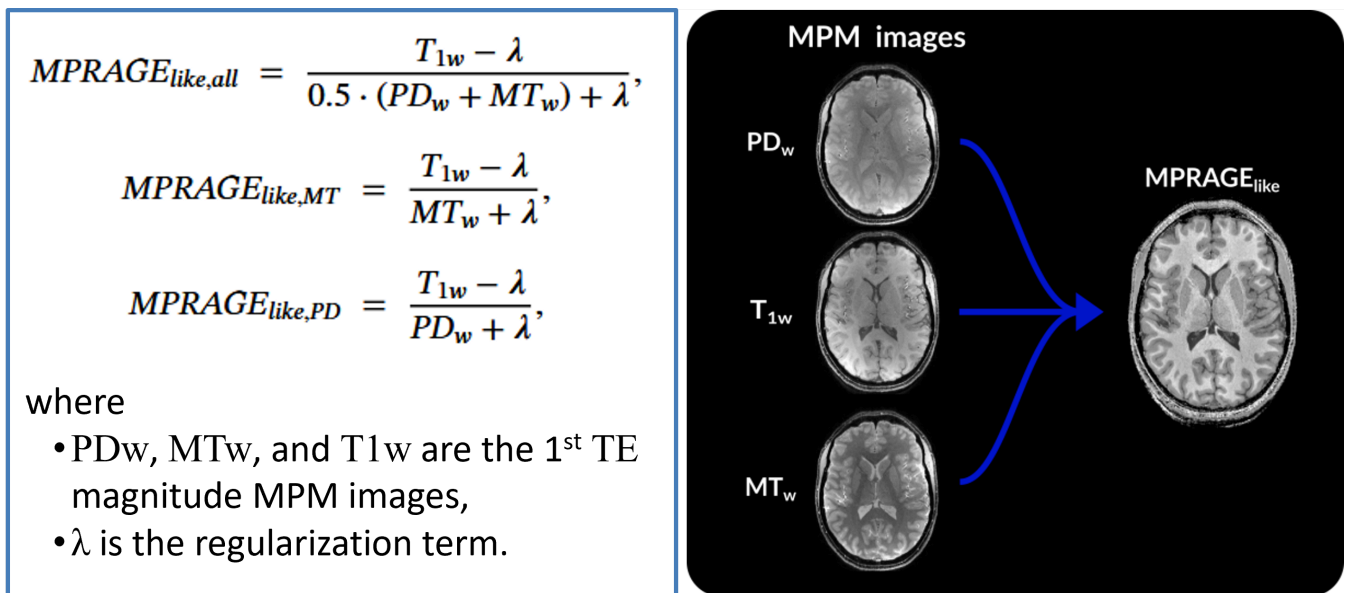
Twenty-three healthy subjects were scanned with the same imaging protocol, including both MPM and MPAGE images at three different 7T sites (Siemens MAGNETOM Terra or MAGNETOM 7TPlus) using universal parallel transmit RF pulses and identical 8Tx/32Rx head coils (Nova Medical, Wilmington, MA, USA). To assess the impact of the value of the regularization term λ on the MPAGElike images, the following λ values were tested: 0, 50, 100, 200, 300, 400, and 500. For all λ values and MPAGElike equations, the voxel-wise relative difference in signal intensity ($\Delta s/s$) between the $\lambda = 0$ image and other λ values was computed. Moreover, to determine an optimal λ , the Structural Similarity Index Metric (SSIM) [5] was computed for each MPAGElike equation and λ with the authentic MPAGE as the reference image, see Figure 2. SSIM was chosen because a metric that would convey a sense of perceived similarity over a pure quantitative similarity was desired, especially since the voxel values of an MPAGE image do not convey any direct quantitative meaning. The value of λ producing the largest average SSIM, averaged across all subjects, is deemed optimal.

This approach to determine the optimal λ value requires a complete dataset, with both MPM and MPAGE images, acquired on multiple subjects. Moreover this calculation should be repeated for each MPM sequence, MRI scanner, and coil set up. Deriving the optimal λ value directly from the T1w, PDw and MTw images, without a tedious calibration phase, would thus facilitate greatly the processing of any "new" dataset. Given the data at hand and the assessment of λ 's influence, we deduced a heuristic approach to directly calculate λ from the image intensity profiles:

1. for all T1w, PDw and/or MTw images, background voxels are masked out, i.e. those with an intensity lower than 80% of the "global" image intensity, as estimated by SPM's `spm_global` function, in all images.
2. the mean of the median intensity of within-mask voxels in each image is calculated.
3. fix λ to be a pre-defined fraction of this mean-of-medians values

The ratio between the optimal λ , found empirically, and this mean-of-medians is directly estimated from our data. This simple approach will at least self-adjust for the scaling to the MPM images and account for their intensity range.

Figure 1:



Results:

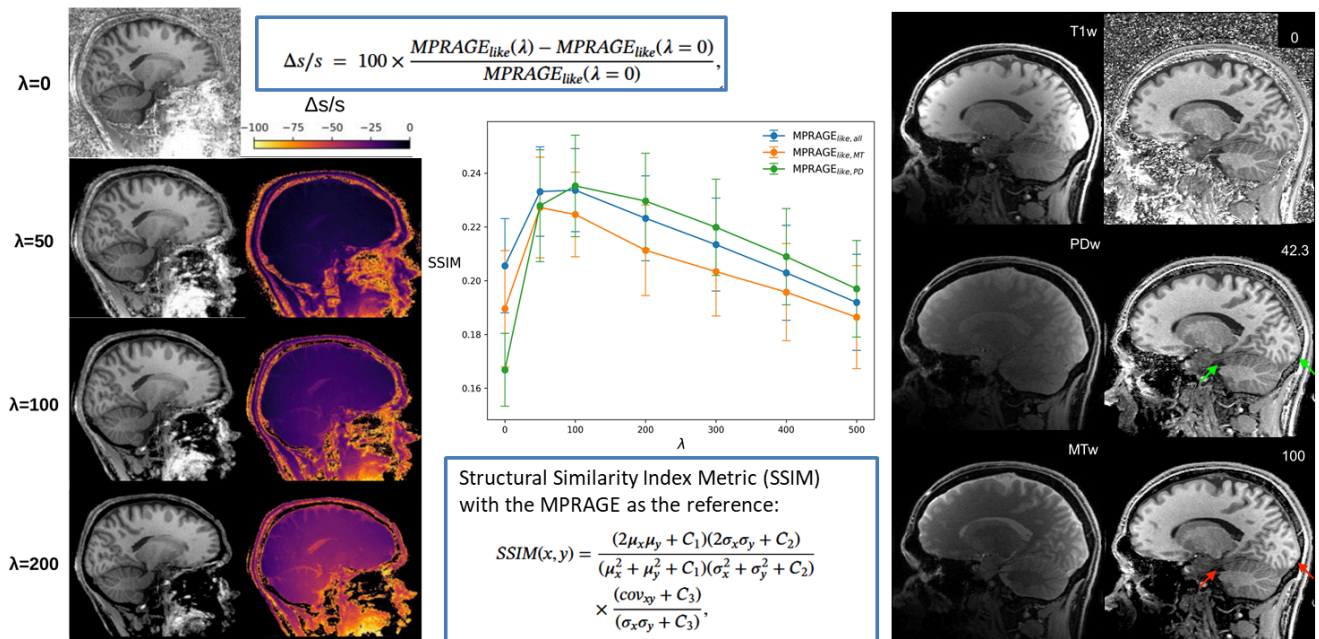
For the data from our 23 healthy subjects, the impact of λ on the MPRAGE_{like} images is shown in Figure 2 (left & centre). Qualitatively, one can observe that with increasing value of λ , the background noise is reduced while the spatial signal inhomogeneity is increased. One visible difference between MPRAGE_{like} images and the MPRAGE was the brightness of blood vessels in the latter compared to the MPRAGE_{like}.

Quantitative comparisons performed using the average SSIM are shown in Figure 2 (centre). The highest SSIM value was reached at $\lambda = 100$ for MPRAGE_{like}, combining all 3 T1w, PDw and MTw images or only T1w and PDw images, and $\lambda = 50$ for MPRAGE_{like}, combining only T1w and MTw images. Based on these results, $\lambda = 100$ was selected as the best regularization term for sufficient background noise suppression while minimally impacting the image contrast. Moreover, combining all 3 T1w, PDw and MTw images or only T1w and PDw leads to higher SSIM values than just using T1w and MTw images. Therefore, if either the PDw or MTw image was of lower quality, e.g. due to movement artefact, one could drop the affected contrast to preserve the quality of the MPRAGE_{like} image.

The mean of the median values of within-mask voxels for each subject's images was about 1000 in our dataset, we thus estimated the ratio between the empirically defined optimal λ value (100) and this mean-of-medians to be 10. We tested the proposed heuristic on a totally different set of images acquired on a Siemens 3T Skyra (32 channel head coil). The observed mean-of-medians was ~ 423 , so we MPRAGE_{like} images with $\lambda = 42.3$ (heuristic optimal) and $\lambda = 100$ (as for the other dataset), see Figure 2 (right). The red arrows, on the MPRAGE_{like} image obtained with $\lambda = 100$, point at areas with too heterogeneous signal or contrast (as happens with too large regularization), whereas the green arrows, on the MPRAGE_{like} image obtained with $\lambda = 42.3$, show the same areas but with reasonably maintained homogeneity and without background noise. This procedure still remains to be more thoroughly validated for other datasets. Nevertheless given the stability of the mean-of-medians calculation and its adaptability to any image intensity profile, one can consider this heuristic to be fairly robust.

Note that more validations of the proposed MPRAGE_{like} technique (in term of 1/ segmentation performance, 2/ signal- and contrast-to-noise ratio, and 3/ comparison with *syn*MPRAGE another tool to generate MPRAGE-like images), were actually performed and are available in [3].

Figure 2:



Conclusion:

We propose an extension to MPRAGElike [3]; a novel and simple technique producing images with synthetic T1w contrast directly from ME-GRE images with different contrast weightings that can be used as a surrogate to MPRAGE for automatic brain segmentation. The results showed that MPRAGElike produces images highly resembling MPRAGE images except for the absent arterial blood highlighting typical at 7T. This makes MPRAGElike a robust new solution for synthetic T1w imaging techniques at UHF-MRI, which has been previously lacking. MPRAGElike would benefit from further validation across different field strengths and within non-healthy cohorts, which the proposed regularization rescaling now allows for. Ultimately, implementing MPRAGElike would allow researchers to skip acquiring an MPRAGE image, resulting in a considerable amount of scan time saved while still being able to run the same quantitative neuroimaging pipelines. Tissue segmentation derived from MPRAGElike can immediately be used for region-of-interest analysis of parameter maps in native MPM space.

Code availability:

Code to generate MPRAGElike images is also provided, both in Python and Matlab:

- original repository with Python code, <https://github.com/mafortin/mprage-like>
- forked repository with Matlab code, <https://github.com/CyclotronResearchCentre/mprage-like>

Note that only the Matlab code includes both automatic image registration and heuristic for optimal λ estimate but it relies on a few I/O functions from SPM package (<https://github.com/spm>). The Matlab code is also interfaced with SPM's `matlabbatch` GUI system, allowing easy pipelining of data processing, and it will be integrated in the hMRI toolbox (<https://hmri-group.github.io/hMRI-toolbox/>).

References/Citations

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Primary & Secondary Parent Category & Sub-Category

Primary

- Modeling and Analysis Methods
- Other Methods

Secondary

- Imaging Acquisition Methods
- Anatomical MRI

Keywords

(up to 10 from a list)

MRI, Open-Source Code, Segmentation, Spatial Normalization
