Machine Learning for Medical and Neuroscientific Imaging

With hardware approaching fundamental safety and economical limits, medical imaging is undergoing a paradigm shift towards intelligent data processing. Machine learning plays a central role in this development.

MR-based Attenuation Correction for PET-MR PET-MR systems combine functional information from Positron Emission Tomography (PET) with structural information from Magnetic Resonance (MR) Imaging and hold much promise for clinical and research applications. They demand the PET attenuation (or μ) map, normally computed from CT, to be determined from MR data, which constitutes an ill-posed problem [3, 1]. We developed a Gaussian process prediction framework, trained on co-registered MR and μ-maps, and evaluated it on brain [4] and whole body [2] data. The paper [4] received a Best Basic Science Investigation Award of the Journal of Nuclear Medicine in 2008. A collaborative effort with the university hospital, Tübingen, the method has been patented and licensed to Siemens AG.

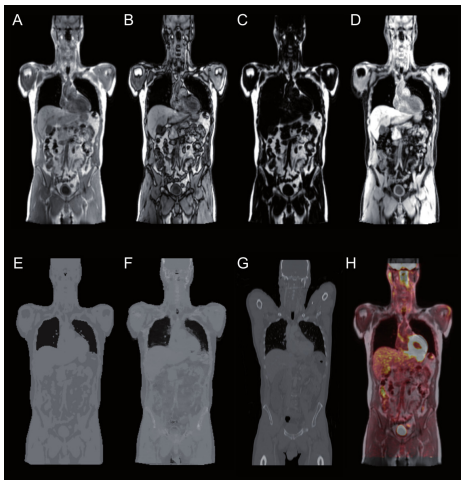

Figure 0.1: Top: MR image (T1-weighted 3D gradient echo sequence). (A) In-phase, (B) opposed phase, (C) fat and (D) water images. Bottom: attenuation maps created from MR image using (E) segmentation method and (F) our machine learning method; (G) corresponding reference CT slice (same patient) and (H) our reconstructed PET image overlaid on In-phase MR image.

Blind Retrospective Motion Correction for MRI Patient motion during long MR scans leads to severe non-local degradations and can render images unacceptable for medical diagnosis. We developed a retrospective (i.e., post-processing) approach called **GradMC**, which operates on the corrupted data [5, 6]. It automatically corrects for rigid motion by searching for a trajectory whose inverse application optimizes a quality metric based on image statistics. The vast search space is explored by multi-level robust gradient-based optimization. The method consistently improves image quality over many motion trajectories. Our GPU implementation processes a full 3D volume in a few minutes, which is acceptable in routine clinical use. In contrast to other techniques (in particular prospective ones), our approach does not lengthen scan time.

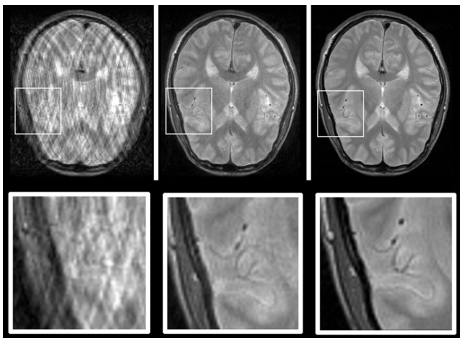

Figure 0.2: Motion correction of 2D RARE images. Freely moving human subject. Left: motion corrupted image. Middle: reconstruction. Right: no-motion image.

MRI Sampling Optimization by Bayesian Experimental Design In Cartesian MRI, straight lines (phase encodes; PEs) are acquired in discrete Fourier (or k) space, with scan time proportional to the number of PEs. With nonlinear "sparse" optimization, good images can be reconstructed from under-sampled k-space, if only the PEs acquired are carefully chosen. We address k-space optimization as a Bayesian experimental design problem, resulting in an efficient optimization algorithm for Cartesian and spiral trajectories [9, 8]. Sequences are optimized sequentially, adding PEs which maximally reduce uncertainty in the reconstructed image. Uncertainty is quantified by way of a sparse linear model, linking image and data acquired so far. This protocol hinges on a novel, large scale approximate Bayesian inference method of ours [7]. On clinical resolution brain image data from a Siemens 3T scanner, automatically optimized trajectories lead to significantly improved images, compared to standard low-pass, equi-spaced or variable density randomized designs.

Publications

Journal Articles

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[3] M Hofmann, B Pichler, B Schölkopf, and T Beyer. Towards quantitative PET/MRI: a review of MR-based attenuation correction techniques. *European Journal of Nuclear Medicine and Molecular Imaging*, 36(Supplement 1):93–104, 3 2009. 1

[4] M Hofmann, F Steinke, V Scheel, G Charpiat, J Farquhar, P Aschoff, M Brady, B Schölkopf, and BJ Pichler. MRI-based attenuation correction for PET/MRI: A novel approach combining pattern recognition and atlas registration. *Journal of Nuclear Medicine*, 49(11):1875–1883, 10 2008. 1

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[9] MW Seeger, H Nickisch, R Pohmann, and B Schölkopf. Bayesian experimental design of magnetic resonance imaging sequences. In D Koller, D Schuurmans, Y Bengio, and L Bottou, editors, *22nd Annual Conference on Neural Information Processing Systems (NIPS)*, pages 1441–1448, Vancouver, BC, Canada, 6 2009. Curran. 1