Title:	**Artificial Intelligence for Multimodal Image Reconstruction**
Position:	Postdoc
Topics:	Image reconstruction; inverse problems; machine- and deep-learning
Institute:	LaTIM, INSERM UMR1101, *Université de Bretagne Occidentale*, Brest, France
Supervisor:	Alexandre Bousse, alexandre.bousse@univ-brest.fr
Head of Department:	Dimitris Visvikis, visvikis@univ-brest.fr
Duration:	2 years with possibility to renew

General Presentation of the Topic Medical imaging is the technique of creating a visual representation of the anatomy or of the function of some organs or tissues. The images are obtained by *tomographic reconstruction*, which is the task of estimating an image from measurement data collected by an imaging system. In computed tomography (CT), the image to reconstruct corresponds to the X-ray attenuation which reflects the proportion of photons interacting with the matter as they pass through the object. In positron emission tomography (PET) imaging, the system detects pairs of γ-photons indirectly emitted from a positron-emitting radiotracer delivered to the patient. The patient dose should be kept to a minimum level. Other medical imaging techniques include for example magnetic resonance imaging (MRI), single photon emission computed tomography, and ultrasound.

The collected data can be affected by poor signal-to-noise ratio (SNR) which translates into degraded image quality. The noise regroups the random phenomena that occur during the acquisition. While shorter acquisitions are preferable not only due to time constraints but also to limit the patient dose, they result in lower SNR. The challenge of image reconstruction is therefore to reconstruct an image from a **short/low-dose acquisition** with **acceptable noise**.

Recent **machine-learning (ML) techniques** for reconstruction have pushed towards less noise: using a training dataset of existing images, (supervised) ML techniques can learn parameters and features that can be used as prior knowledge within a model-based iterative reconstruction (MBIR) framework. [1]–[3]. More recently, deep-learning (DL) techniques have been used to achieve complete image reconstruction using a raw data training dataset [4]. By combining the measurements with the information from a training dataset, ML techniques offer the possibility to further reduce the patient dose and acquisition time without degrading the image quality.

Objective of the Postdoc Learning-based methods are still very new and their utilisation are mostly limited to single images. More specifically, they could benefit from the utilisation of multimodal data by exploiting the information of the combined modalities. Multimodal imaging plays an important role in accurately identifying the diseased and the normal tissues. CT images are generally used for treatment planning, and MRI provides better soft-tissue definition, while PET images are useful in identifying the disease at a metabolic level even before it is visible on CT or MRI. *Multimodal machine learning* (MML) aims at building models that can process and relate information from multiple modalities. Learning from multimodal sources offers the possibility of capturing correspondences between modalities and improve SNR, thus allowing for noise reduction.

In this project we will develop **new MML reconstruction techniques** for multimodal imaging system such as hybrid positron emission tomography/computed tomography and hybrid positron emission tomography/magnetic resonance imaging, with the possibility of utilising time-of-flight PET data. Other image modalities such as spectral CT can be considered. The hypothesis is that combining the raw data from different modalities with machine-learned multi-modal atoms can reduce the noise and improve the image quality. More specifically, the tasks are:

- to develop new ML and DL for multimodal dictionary learning;
- to apply these new dictionaries for MML reconstruction.

The utilisation of ML for multimodal imaging is an open problem that has only been addressed in prototype methodologies with joint convolutional kernels [5] or coupled dictionaries [6]. Image reconstruction will be achieved with standard MBIR with ML-derived information. Alternatively, DL techniques will also be considered to reconstruct from multimodal raw data.

Profile Required

- PhD (or equivalent) in Applied Mathematics, Computer Science, Signal an Image processing, Biomedical Physics
- Skills in computer science, compressed sensing and machine/deep-learning
- Programming: C++, Python, Matlab

Contact alexandre.bousse@univ-brest.fr

References

[1] S. Ravishankar and Y. Bresler, "L0 sparsifying transform learning with efficient optimal updates and convergence guarantees," *IEEE Transactions on Signal Processing*, vol. 63, no. 9, pp. 2389–2404, 2015.

[2] S. Ravishankar, R. R. Nadakuditi, and J. A. Fessler, "Efficient sum of outer products dictionary learning (SOUP-DIL) and its application to inverse problems," *IEEE Transactions on Computational Imaging*, vol. 3, no. 4, pp. 694–709, 2017.

[3] I. Y. Chun and J. A. Fessler, "Convolutional analysis operator learning: Acceleration, convergence, application, and neural networks," *arXiv preprint arXiv:1802.05584*, 2018.

[4] Y. Li, K. Li, C. Zhang, J. Montoya, and G.-H. Chen, "Learning to reconstruct computed tomography (CT) images directly from sinogram data under a variety of data acquisition conditions," *IEEE Transactions on Medical Imaging*, 2019.

[5] K. Degraux, U. S. Kamilov, P. T. Boufounos, and D. Liu, "Online convolutional dictionary learning for multimodal imaging," in *2017 IEEE International Conference on Image Processing (ICIP)*, IEEE, 2017, pp. 1617–1621.

[6] P. Song, L. Weizman, J. F. Mota, Y. C. Eldar, and M. R. Rodrigues, "Coupled dictionary learning for multi-contrast MRI reconstruction," *IEEE Transactions on Medical Imaging*, 2019.