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SPARSE RECOVERY IN MYOCARDIAL BLOOD FLOW QUANTIFICATION VIA PET

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Introduction: Dynamic PET (positron emission tomography) can be used to analyze physiological processes over time, e.g., myocardial blood flow. Therefore, the PET data need to be separated into temporal bins. A simple way reconstructing dynamic PET data is to compute a standard EM reconstruction for each temporal bin, with the obvious drawback of neglecting the temporal correlation between the bins. One way to overcome this problem is to incorporate mathematical models for the analysis of the tracer activity over time into the reconstruction process. The aim of our work is to show how sparsity methods can be use in the framework of kinetic modeling to improve dynamic PET reconstructions.

Methods: We are using a linear model operator developed by Reader et al., which is based on a one-compartment model. The operator consists of the input curve, exponential basis functions and their associated coefficients. The basis functions depend on a set of possible perfusion values, which is assumed to be large. Assuming the input curve to be known, we are interested in recovering the coefficients via a variational formulation. Furthermore, we assume the „true" perfusion value to be contained in the set of possible perfusion values, so we are interested in only one coefficient corresponding to the true perfusion value, which gives rise to use sparsity methods. In a general variational formulation we have several possibilities of choosing the fidelity and regularization term. One reasonable choice for the fidelity term is, of course, to use the Kullback-Leibler divergence, to use the information that the radioactive decay follows a Poisson process. Another possibility is to use a weighed l^2 fidelity term, that can be derived by approximating the Kullback-Leibler fidelity. For the regularization we are actually interested in finding a sparse solution for each pixel (we want to recover the one basis function that corresponds to the perfusion for that pixel), so we want to have a regularization like $l^{1,\infty}$. But one could also use an EM-TV regularization on the coefficients to identify the largest coefficient.

Results: The ideas above have been tested on both synthetic and real data. The real data are from a dynamic PET scan with radioactive water being the tracer, thus, showing a low signal-to-noise ratio. The synthetic data have been simulated to show a similar behavior. In both cases, the quality of the reconstructions are higher (i.e. less noise, more details) than by reconstructing each temporal bin independently.

Conclusions: The proposed method improves dynamic PET reconstructions by including the temporal correlation between the datasets through a mathematical model.

Acknowledgement/References: M. Benning et al., A Nonlinear Variational Method for Improved Quantification of Myocardial Blood Flow Using Dynamic H2150 PET, 2008. G.T. Budinger et al., Dynamic single photon emission computed tomography --- basic principles and cardiac applications, 2010. A.J. Reader et al., Fully 4D image reconstruction by estimation of an input function and spectral coefficients, 2007. A. Sawatzky et al., Accurate EM-TV Algorithm in PET with low SNR, 2008. M.N. Wernick et al., Emission Tomography: The Fundamentals of PET and SPECT, 2004.