

MR-based PET Attenuation Correction for Brain PET-MR Using Support Vector Machines

Yicheng Chen¹, Di Cui^{1,2}, Yingmao Chen³, Jinsong Ouyang⁴, Georges El Fakhri⁴, and Kui Ying¹

¹Key Laboratory of Particle and Radiation Imaging, Ministry of Education, Department of Engineering Physics, Tsinghua University, Beijing, Beijing, China,

²Department of Diagnostic Radiology, The University of Hong Kong, Hong Kong, China, ³Department of Nuclear Medicine, The general hospital of Chinese People's Liberation, Beijing, China, ⁴Department of Radiology, Division of Nuclear Medicine and Molecular Imaging, Harvard Medical School and Massachusetts General Hospital, Boston, Massachusetts, United States

Target audience:

Researchers and clinicians interested in quantitative PET in hybrid PET/MR systems.

Purpose:

After the successful integration of MR and PET hardware, PET attenuation correction remains the main unsolved challenge facing PET-MR¹. Several methods combined with machine learning such as pattern recognition² and neural network³ have been proposed to calculate attenuation map from MR scans for PET/MR systems. In this work, we proposed a support vector machine (SVM) regression method for generating pseudo-CT from MR information. The proposed method was compared to Gaussian mixture regression (GMR) model method⁴, which also generates continuous pseudo-CT images.

Methods:

Patient Data: Eight patient data sets were used in this study. Each data set includes 1 T2-TSE MR (TE: 87ms, TR: 4540ms, Flip angle: 150°, matrix size: 640×616×23), 2 Ultra-short TE (UTE) MR (TE: 0.07/2.46ms, matrix size: 192×192×192) and 1 CT (120kVp, 100mAs, matrix size: 512×512×45) image volumes. The UTE sequences were used to distinguish bone and air in MR images in order to give better boundaries. For each patient, the following steps were performed. First, SPM was used to register CT, UTE1 and UTE2 to T2. Second, MR and CT image volumes were normalized to 0~1 range for SVM training. Third, a head mask was obtained from T2 using a region growing method.

Six and the other two patient data sets were used for training and testing, respectively. LIBSVM⁵ software in Matlab was used for SVM regression. ε-SVR (epsilon support vector regression) was selected as the SVM formulation. Intensity of each voxel and its eight neighborhood voxels of the three MR images were used as input to SVM to obtain the CT value for the voxel (Fig. 1). Both the training and testing were performed slice by slice. GMR method is performed by aligning the voxel intensity, mean value and standard deviation of each neighborhood as input and training the model of 20 multivariate Gaussians.

Results:

Fig.2 (A) shows the pseudo-CT images together with the real CT image. Fig.2 (B) shows the bias images for the SVM and GMR methods using the real CT image as the gold standard. SVM yields 33.85% and 16.89% lower MSE values than GMR on average for test patient 1 and 2, respectively.

Discussion and Conclusions:

A SVM method to predict continuous attenuation map from T2 and UTE MR Images was presented. The SVM method appears to produce less bias than GMR and may have potential to improve PET quantitative accuracy for PET-MR imaging. Further research can be conducted by increasing the training data set volume and optimizing the feature design.

References:

1. Wagenknecht G, et al, Magn Reson Mater Phy. 2013;26 (1): 99-113.
2. Hofmann M, et al. JNM. 2008;49 (11): 1875-1883.
3. Santos Ribeiro A, et al. Nucl Instrum Meth A. 2013;734: 166-170.
4. Johansson A, et al. Med Phys. 2011;38 (5): 2708.
5. Chang CC et al. LIBSVM software. <http://www.csie.ntu.edu.tw/~cjlin/libsvm>

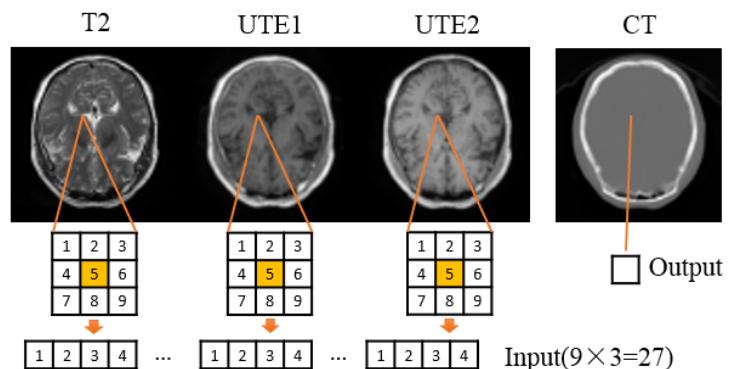


Fig 1 Regression input and output demonstration.

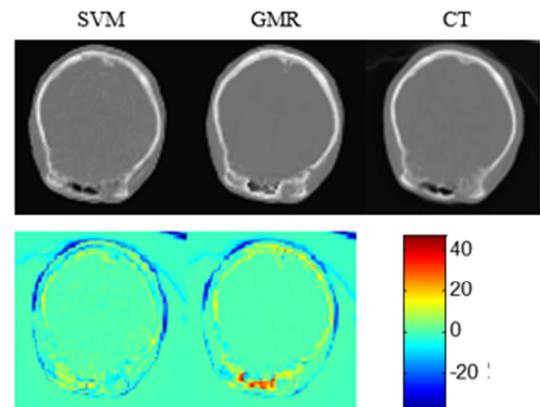


Fig 2 (A) Comparison of the SVM predicted attenuation map, GMR map and gold standard CT map for one of the test patients. (B) Bias images (in percentage).