Attenuation correction for PET/MR using continuous pseudo-CT derived from MR T1w and population CT images

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Introduction

An integrated PET/MR system that allows simultaneous acquisition of both MR and PET images offers a unique opportunity to study various diseases by taking advantage of PET's sensitivity to physiology and MR's capability of high resolution anatomic imaging. MR-based attenuation correction (AC) is a prerequisite to fully harnessing the power of the recently introduced hybrid PET/MR scanner. In a PET/CT scan, CT signal in Hounsfield unit is scaled up to 511 KeV using a piecewise bilinear method for PET attenuation correction [1, 2]. This method has been regarded as the current gold standard. In contrast, AC is challenging for PET/MR because there is no simple relationship between the proton density and relaxation time-based MRI signal and the electron density information required for PET AC. AC errors are mainly caused by mis-assignment of AC coefficients, particularly in regions of bone and air due to almost indistinguishable MR signal in most MR scans. In this study, we sought to develop an approach to estimate continuous pseudo-CT (pCT) images from MR T1w images for PET AC in the head. Furthermore, we evaluated the performance of our proposed method against the gold standard – scaled CT (CTScl) AC. Accuracy in AC was compared among several approaches.

Materials and Methods

Since there is no one-to-one correspondence between MR and CT signal, continuous pCT images may be derived from MR images with a pattern recognition approach through learning the mapping function from MR to CT using population data[3]. The premise of this approach is that morphological resemblance between the MR images of a subject and the MR images from a population can be utilized to estimate pCT images of that subject from the population CT. We refer the subject whose CT is to be estimated as the template and the remaining subjects as atlas elements. A typical population based method usually performs an image registration to align all other atlas elements onto the template images and the mean CT signal at a correspondent location from all aligned atlases elements will be assigned as the pCT signal for the template. In this study, we refer this method as the MeanAtlas method. It is conceivable that each atlas element should not contribute equally to the template pCT signal because some of atlas elements may resemble more closely with the template while others do not at different anatomic locations. To this end, we propose a sparse regression (SR) method to select patches from atlases that can yield a more relevant representation of local structures of the template. Since only MR T1w images were used to derive pCT in this study, a separation between air and bone, which are often in close proximity in head, is still challenging. To overcome this problem, we propose to use an air space probabilistic map from all the aligned atlases to define a candidate air space and a hidden Markov random field segmentation (hMRFS) method was utilized to segment air only in this candidate air space.

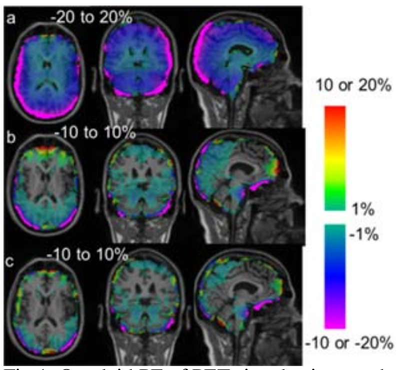

Fig 1. Overlaid PE of PET signal using vendor provided dixon (a), the MeanAtlas (b) and the our PASSR (c) methods. Absolute %errors below 1% are not shown in color. Color bar ranges are +/-20% for the dixon method (a), and +/- 10% for the proposed PASSR method.

Data acquisition PET/MR/CT image were obtained from 19 patients in this study with an approval IRB and signed consent. F^{18} Florbetapir (Amyvid [Avid]) PET images and T1 MPRage images were acquired using a hybrid MR/PET system (Biograph mMR, Siemens, Erlangen, Germany). CT images were acquired using a PET/CT system (Biograph 40 PET/CT, Siemens, Erlangen, Germany).

Data analysis For any given template, the MR/CT/air maps (from CT segmentation) from the remaining 18 subjects (atlas) were aligned to the template's T1 image via a nonlinear diffeomorphic registration algorithm[4]. Air probalistic map was generated as the frequency of labeled air from all aligned atlas. Regions with air probability greater than 20% were considered as candidate air space. Within this candidate air space, an air/tissue two-class segmentation was performed to identify the final air space using a hMRFS method. Within the non-air regions, local patches were selected in the vicinity of a voxel and a SR was utilized to select the most relevant patches from a large group of candidate patches. Of note, SR was trained using only T1w images. The obtained SR coefficients were then applied to atlas CT images to derive pCT for the template. AC maps were then created using bilinear piecewise scaling using the pCT. We refer our proposed method as Probalistic Air Segmentation and Sparse Regression (PASSR) method. Customer AC maps were aligned with the acquired PET in space and incorporated into a vendor provided PET image reconstruction software (e7tools, Siemens) for AC as well as scatter correction in PET recon using the ordered subsets expectation-maximization (OSEM) algorithm. To evaluate the performance of the proposed PASSR AC method, CTScl was used as the gold standard to compute the %AC error (PE) map as $(PET_{PASSR}-PET_{CTScl})/\ PET_{CTScl}*100$. Mean absolute PE (MAPE) was computed as the mean(abs(PE)) across the whole brain. Paired t-test was used to compare MAPE in the PASSR, MeanAtlas and the vendor provided Dixon (bone is not considered in the Dixon method) AC PET images. Moreover, % voxels that have within +/- 2% and +/- 10% AC errors were computed.

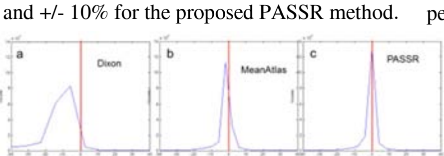

Fig 2. Histograms of PE in AC using the Dixon (a), MeanAtlas (b), and PASSR methods (c). Zero PE is marked by a red vertical line.

Results

Due to different proximity to skull and air space, spatially varying AC errors were found (Fig 1) across the whole brain. In general, cortex region has more AC errors than the deep brain. Without correcting for the attenuation exerted by bone, the Dixon method has a substantial underestimation of PET signal (Fig. 1a). Both MeanAtlas and PASSR methods significantly reduced the AC PE (Fig. 1b and c) with the PASSR method showed the least PE across the whole brain. Of note, due to the large errors in the dixon method, the color bar dynamic range increased from (-10%, 10%) to (-20%, 20%) for the Dixon method in Fig. 1a to avoid color saturation. The whole-brain MAPE of our PASSR method was 2.49±0.9%, which was significantly lower than the Dixon (11.79±2.09%, $P<10^{-6}$) and the MeanAtlas methods (2.73±1.0%, P<0.01). Histograms of AC PE showed that our PASSR method not only has a lower whole brain MAPE, but also has a narrower PE distribution than both the Dixon and MeanAtlas methods (Fig. 2). Significantly more imaging voxels (67.3±16.5%) have within +/- 2% PE using the PASSR method than the Dixon (7.5±2.1%, $P<10^{-6}$) and the MeanAtlas (64.1±16.8% , P=0.02). More voxels have within +/- 10% PE using the PASSR methods (96.1±1.3%) when compared to the Dixon (58.7±13.6%, P=0.01) and MeanAltas (95.7±16.5%, P=0.06) methods.

Discussion and Conclusions

AC using PASSR method reduced not only the mean PE across the whole brain but also the extent of spatially varying errors when compared to the Dixon and MeanAtlas methods. Two unique features of our PASSR method are advantageous, 1) employing SR to select highly relevant patches to enhance the local structure similarity; and 2) using air probabilistic maps from population data to improve the separation between air space and bone using only T1w images. Of note, using T1w MR images alone, we are able to achieve accuracy on a par with the previous multispectral MRI methods. Future work includes integration of UTE bone and air signal into the SR to further improve the AC accuracy.

References

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