EXAMPLE BASED BRAIN MRI SYNTHESIS

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Target audience

This work is intended for people who are interested in the methodology or applications of synthetic brain MR images.

Purpose

Most current MR simulation methods[1-3] are based on simplifications of MR physics and lack realism in the resulting images. The purpose of this work is to develop an example based simulation method that implicitly learns the physics of the MR acquisition using a patch-based regression. Because the realistic brain MR images are synthesized from a known anatomical model, they are useful for validating image segmentation and other processing algorithms.

Methods

The N3-corrected[4] MPRAGE image of a healthy subject from the KKI data set[5] is chosen as the atlas image (Fig.1(a)). To prevent the intra/inter-rater variability of manual delineation or any bias towards a single automatic approach, we apply a set of publicly available segmentation algorithms (1.ATROPOS[6] 2.FAST_no_pve[7] 3.FAST_pve[7] 4.Freesurfer_EM[8] 5.SPM[9] 6.Freesurfer[8] 7.Lesion_Toads[10] 8.LoAd[11] 9.FIRST[7]) on the skull stripped[12] image and then fuse the segmentation results. Methods 1-5 generate 3-class segmentation labels {1=CSF, 2=GM, 3=WM}, methods 6-8 generate multi-class segmentation labels which are grouped into {1=CSF, 2=cortical GM, 3=WM, 4=subcortical GM}, and method 9 generate labels (ignoring the brainstem) within subcortical GM which are grouped into {4=subcortical GM}. In the segmentation fusion, subcortical GM label is assigned to a voxel if methods 6-9 all classify this voxel as subcortical GM, otherwise, majority-voting on methods 1-8 is used to determine the label. Using the fused segmentation (Fig.1(b)) as initialization, a Fuzzy C-means clustering with membership smoothing[13] is applied on the skull-stripped image I, resulting in four membership images $\{F_i\}$. These membership functions, which are continuously valued between zero and one, allow better modeling of the partial volume effect on the anatomy. In addition, the same clustering is applied on the non-subcortical image $I_n=I*(1-M)$ with the same initialization excluding subcortical GM, where M is the binary mask of subcortical GM. The resulting three membership images $\{T_i\}$ are combined with $\{F_i\}$ to generate final memberships $P_i=T_i+F_i*M$ (Fig.1(c-f)), where $i=\{1,2,3,4\}$ represent the 4-class segmentation labels and $T_4=0$. Note that subcortical GM is well separated from WM using the above two-phase clustering method. For the non-brain part, there is no strict definition of the anatomical model, and we simply apply a 3-class FCM to generate three membership images (Fig.1(g-i)). A patch based regression ensemble[14] was trained to learn the relationship between the atlas image and its seven anatomical membership images at each voxel. The membership images of a given image can be constructed in the same way and used as input for the previously the trained regression ensemble to build a new synthetic image.

Results

Fig.2 (a) shows the MPRAGE image of another subject in KKI data set. The image synthesized by our method (Fig.2 (b)) using the membership images generated from Fig.2(a) is compared with the result from the physics based method[1] (Fig.2 (c)) using the same membership functions as weights. Visual inspection shows that our result looks almost as realistic as the original image while the physics based simulation looks more artificial. After each image in Fig.2(a-c) is normalized to the intensity range [0,1], the RMS error between our result and the original image is 0.012, while the error between the physics based simulation and the original is 0.075.

Discussion

Besides the demonstrated MPRAGE synthesis, the proposed example based mechanism can be applied to predict other structural image contrasts such as T2-weighted images, as long as those modalities are available for the atlas subject. This method can also be applied to anatomical models derived from manual segmentations.

Conclusion

This work proposes an example-based MR synthesis method. Initial results on MPRAGE synthesis shows our result looks more realistic than a physics based simulation. Further development of the synthesis framework to generate images with varying noise and inhomogeneity levels is to be performed in the future.

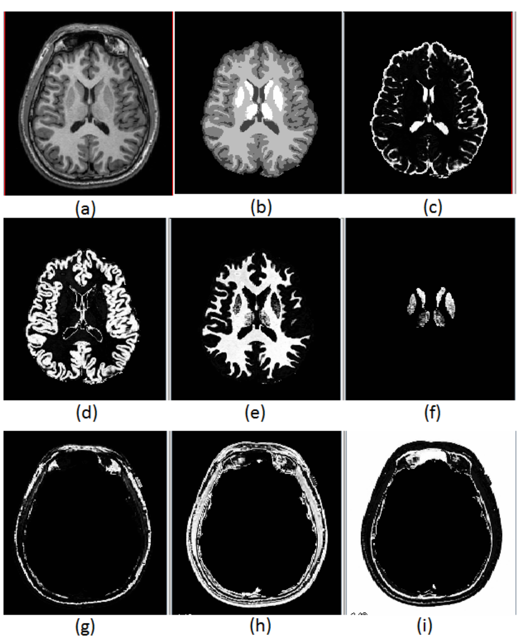

Fig.1 (a) atlas MPRAGE image; (b) segmentation fusion result; (c-i) membership images of CSF, cortical GM, WM, subcortical GM and non-brain area

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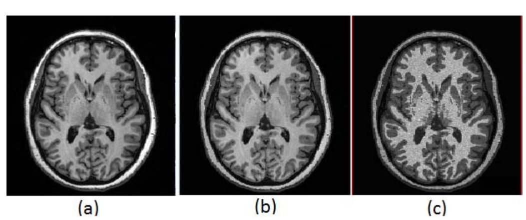

Fig.2 (a) MPRAGE image of a KKI subject; (b) synthetic image using our method; (c) physics based[1] simulation result