Longitudinal Changes of White Matter Lesions

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INTRODUCTION: Quantification of white matter lesion progression is of major interest in MR imaging of the human brain for the diagnosis and monitoring of several diseases like Multiple Sclerosis or Alzheimer's disease. T1 (T1w) and T2 (T2w) weighted images may provide insufficient tissue contrast for accurate segmentation of lesions. The Fluid Attenuated Inversion Recovery (FLAIR) sequence is often used to address this problem, as it provides superior contrast for the detection of lesions. Unfortunately, FLAIR images are not always available, especially in retrospective studies involving older MR data sets. In this work, we synthesize FLAIR contrast images from corresponding T1w and T2w images, enabling lesion detection consistent with that achieved with T1w + FLAIR images. Using our synthetic FLAIR images, we quantify progression of lesions in subjects from the Baltimore Longitudinal Study on Aging [3], which only possess FLAIR sequences

Subject: f $f_n(i)$ $g_n(j)$ $g_n(j)$ $f_n(i)$ Synthetic FLAIR: \hat{f}_n

Figure 1: Synthetic FLAIR from a set of T1w and T2w images.

METHODS: We build upon the idea of image hallucination [1] to synthesize FLAIR images from a set of T1w and T2w images. Suppose f_{T1} and f_{T2} are T1w and T2w images of a subject. If f_{FL} is the FLAIR modality, then, $f_{\rm FL} = W(f_{\rm T1}, f_{\rm T2}, \theta)$, where W is the imaging process, θ is the intrinsic acquisition parameters like repetition time, flip angle etc. Given all these underlying parameters, it is possible to directly estimate $f_{\rm FL}$ [4]. For most studies, θ is not known and W is difficult to model, prohibiting direct estimation of a FLAIR. Instead we use an atlas based approach to synthesize FLAIR. We assume we are provided or can obtain an atlas, defined as a set of co-registered images $A = \{g_{T1}, g_{T2}, g_{FL}, h_L\}$, acquired from a model subject that is different from f but also possesses lesions, where g_{T1} , g_{T2} , g_{FL} and h_L are T1, T2, FLAIR images and hard segmentations of lesions, respectively. Also assume that the images are composed of 3D patches $f_{\mathrm{TI}}(i), f_{\mathrm{T2}}(i), g_{\mathrm{TI}}(j), g_{\mathrm{T2}}(j), g_{\mathrm{FL}}(j),$ centered at $i \in \Omega_f$, $j \in \Omega_g$ voxels where Ω_f and Ω_g are image domains of f and g respectively. We synthesize the FLAIR image $\hat{f}_{\rm FL}$ by matching patches of $f_{\rm T1}$ and $f_{\rm T2}$ to the atlas g_{T1} and g_{T2} , taking the resulting patch from g_{FL} . Fig. 1 visually depicts the algorithm flow. From the subject f, we take the i^{th} patch pair $\{f_{T1}(i), f_{T2}(i)\}$ and identify the best possible matching pair $\{g_{T1}(i), f_{T2}(i)\}$ $g_{T2}(j)$; $j \in \Omega_g$ }. The corresponding FLAIR patches $\{g_{FL}(j), j \in \Omega_g\}$ are combined using a non-local means approach [5] to generate the synthetic FLAIR patch $\hat{f}_{\rm FL}(i)$. The merging of all such patches generates the synthetic FLAIR $\hat{f}_{\rm FL}$.

RESULTS: We used this method to synthesize FLAIR images for a longitudinal dataset, which has only T1w and T2w images for older time points and FLAIR for newer time points. We use a validated multichannel lesion segmentation tool [2] to find lesions. To validate the synthetic FLAIR image, we use the lesion segmentation from T1w and true FLAIR as a reference standard and compare the segmentation from T1w and synthetic FLAIR with this reference standard. The Dice between the segmentation obtained from T1w+T2w (Fig. 2) with the reference is 0.51, while it is 0.69 between the reference and the segmentation obtained from T1w+synthesized FLAIR (Fig. 2). Clearly, the synthetic FLAIR yields a segmentation more consistent with using real FLAIR images. Then we plot the evolution of lesions on another normal subject taken from the BLSA dataset [3]. There are 11 consecutive scans of the subject, and each of the scans is comprised of a T1w and a T2w image. Volumes of the first 10 years are registered to the 11th year by an affine registration. Then FLAIR images are synthesized for each year using another

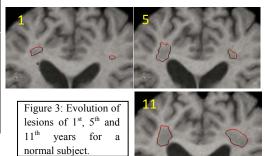
subject as atlas. The lesions are determined by applying the segmentation tool to the T1w and FLAIR images. Fig. 3 shows lesion contours of the year 1, 5 and 11. It can be seen that lesion volumes are increasing. We used the same idea on a pool of 20 normal subjects with atlas as one subject, which is not included in the cohort. Subjects who have clear lesions at baseline and have more than 7 years of scan are selected for analysis of longitudinal progression. The lesion volumes are normalized by the corresponding intracranial volume (ICV) to produce lesion fractions and are plotted in Fig. 4.

CONCLUSION: We have developed a method to synthesize FLAIR images from T1w and T2w images. It is used to find longitudinal growth of lesions in the absence of an appropriate lesion distinguishing contrast. This method can potentially be seen to reduce data acquisition. In a longitudinal study, given T1w and T2w images, acquisition of FLAIR of all the subjects of all the years can be avoided, if it is acquired on a few subjects, which act as atlas.

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Figure 2: Top row shows the true FLAIR, T2w and synthesized FLAIR. Bottom row shows the lesion segmentation obtained using T1w and real FLAIR, T1w and T2w, and T1w and synthetic FLAIR.

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Longitudinal Measurement of Lesion Load

Lesion Load

Age

Figure 4: Plot of lesion load vs age for 20 normal subjects. It is seen that the lesion load increases with age. Red lines are a linear fit of the lesion volumes.