DTI-MRI Augmentation for GBM Tumour Segmentation

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Abstract
Glioblastoma multiforme (GBM), the most aggressive primary brain tumour which has no cure as the survival times are close to the worst of any cancer. Diffusion tensor imaging (DTI-MRI or DTI) is rarely used in diagnosis procedure while it provides specific information about the tumour physiology by visualising its p and q maps. In this paper, our aim was to develop a tool to automate the segmentation of p and q maps using deep learning, therefore, due to the limitation of data per patient, data augmentation (DA) is used to provide ten different combinations of them to improve the segmentation outcome.

Keywords: GBM, deep learning, data augmentation, DTI, MRI.

1. Introduction
Glioblastoma multiforme (GBM) is the deadliest type of brain tumour with no cure. Survival rate of Glioblastoma in England for over 70% of patients is less than 12 months of diagnosis (Brodbelt et al., 2015). However, fit patients who undergo aggressive multimodal therapy may live for longer periods of time, with two year survival rates of 24% being reported in meta-analysis (ala, 2008). Despite the advances in the treatment as well magnetic resonance imaging (MRI) development to monitor tumour, most patient will still die from tumour invasion into healthy brain cells. By having more information about GBM, a better treatment plan can be made to not only visualise the tumour but also its related boundaries better such as potential recurrence areas. For automatic brain tumour segmentation, having many different MR modalities help to improve the segmentation. However, due to the limitations of annotated medical images, data augmentation (DA) techniques are usually used. In this paper we present generating new data information for the same patient by using diffusion tensor imaging (DTI). DTI is a type of MRI which determines physiological features of GBM by visualising its different maps. The DTI abnormality can predict the sites of tumour progression (Price et al., 2006) and decomposition of the diffusion tensor into isotropic(p) and anisotropic(q) components can provide spatial maps of tumour infiltration zones which correlate to the time of tumour progression (Mohsen et al., 2013). DTI-p and DTI-q in combination with other MR sequences is better than conventional MRI for assessing tumour infiltration beyond the gross tumour volume. In this paper, we present DTI augmentation of its p and q maps into ten augmented combination of them to improve the tumour and recurrence region segmentation. The 3D convolutions neural network (CNN), DeepMedic (Kamnitsas et al., 2017), is used to segment the tumour on p and q maps separately and in combination of the augmented images. As a result, the augmentation data combined with p and q maps show improvement in segmentation results.

2. Methodology

DTI images are reconstructed from diffusion-weighted magnetic resonance imaging (DWI or DW-MRI), which is an imaging technique aiming to the mobility of water within the brain. These derived quantities are the isotropic and anisotropic components of the diffusion tensor, respectively called $p$ and $q$, and defined as follows. To model diffusion in white tracts, the diffusion tensor is shaped as a 3x3 matrix, with eigenvalues $\lambda_1, \lambda_2,$ and $\lambda_3$, then:

\begin{align*}
    p &= \sqrt{3D} \\
    q &= \sqrt{(\lambda_1 - D)^2 + (\lambda_2 - D)^2 + (\lambda_3 - D)^2}
\end{align*}

where $D$ is the mean diffusivity: $D = \frac{1}{3}(\lambda_1 + \lambda_2 + \lambda_3)$.

Figure 1 visualises the difference of $p$ and $q$ maps as well as their combinations for the data augmentation purposed. The $p$ and $q$ images are having two contours in blue and red colour which are referring to the $p$ mask and $q$ mask respectively.

![Figure 1: Top row: $p$ mask in blue and $q$ mask in red colour mapped on $p$ and $q$-maps. Bottom rows: 10 combinations of $p$ and $q$ maps used for segmenting tumour boundaries related to $p$ and $q$ masks.](image)

For the segmentation DeepMedic is used, which is a 11-layer, multi-scaled 3D CNN architecture which has been applied in many challenging lesion segmentation tasks, including traumatic brain injuries, brain tumours, and ischemic stroke lesions (Kamnitsas et al., 2016, 2017).

3. Results and Discussion

The proposed method was validated on the clinical dataset, P309, which was collected at Cambridge Addenbrookes Hospital in 2013 funded by both NIHR and CRUK. This dataset
consists of p and q images for 80 patients with different levels of high grade glioma (HGG) and low grade glioma (LGG). These images have two separate manual segmentations corresponding to each modality delineated with expert clinicians using the 3D slicer application (Fedorov et al., 2012) which has been used as the ground truth. Each subject in our dataset has the volume of $240 \times 330 \times 23$ pixels and a voxel size of $0.977mm \times 0.977mm \times 1mm$ in nifti format.

DeepMedic was applied in six different experiments to prove the importance of DTI for better understanding of Glioma. The patients numbers of training, validation and test sets were set to 40, 10 and 30 respectively. Table 1 shows the models by considering different ground truths for the training sets and the relevant Dice coefficient (DC). The number of images (#) per experiment is shown per different model. Model 1 and 2 use only p and q maps respectively for training to segment p and q masks separately. Model 3 and 4 use the p and q maps together which demonstrate slight improvement compared to one channel models. Our proposed models are Model 5 and 6, which are ten augmented combination of p and q shown in Figure 1 to provide DeepMedic more information to learn p and q masks, and the DC shows the improvement compared to other models with less input channels.

Table 1: Dice coefficient performance of modified DeepMedic for different models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Images</th>
<th># Mask</th>
<th># Training</th>
<th># Validation</th>
<th># Test</th>
<th>Average train DC</th>
<th>Average test DC</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>p</td>
<td>p</td>
<td>920</td>
<td>230</td>
<td>690</td>
<td>0.42</td>
<td>0.37</td>
</tr>
<tr>
<td>2</td>
<td>q</td>
<td>q</td>
<td>920</td>
<td>230</td>
<td>690</td>
<td>0.46</td>
<td>0.36</td>
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<tr>
<td>3</td>
<td>p and q</td>
<td>p</td>
<td>1840</td>
<td>460</td>
<td>1380</td>
<td>0.51</td>
<td>0.49</td>
</tr>
<tr>
<td>4</td>
<td>p and q</td>
<td>q</td>
<td>1840</td>
<td>460</td>
<td>1380</td>
<td>0.37</td>
<td>0.38</td>
</tr>
<tr>
<td>5</td>
<td>p, q and 8 DA combination</td>
<td>p</td>
<td>9200</td>
<td>2300</td>
<td>6900</td>
<td>0.62</td>
<td>0.60</td>
</tr>
<tr>
<td>6</td>
<td>p, q and 8 DA combination</td>
<td>q</td>
<td>9200</td>
<td>2300</td>
<td>6900</td>
<td>0.57</td>
<td>0.58</td>
</tr>
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</table>

The improvement of using ten augmented combination of p and q maps improve the segmentation results due to having more data. DTI is made from single scan per patient but the ability of generating different maps of it based on combining isotropic and anisotropic information embedded in them can lead into great source of data to improve the deep learning training. By considering other clinical MR images such as T2, FLAIR and T1 scans these results can be improved but we wanted to show in this paper the improvement of p-q segmentation by only using one scan regardless of having other scans and avoid the trouble of registering them to each other.

4. Conclusions

Segmenting GBM and its recurrence boundaries is a very challenging area as the image modalities are restricted to conventional MRI before treatment. Although the outcome of treatment in GBM demonstrates the lack of information on used MR images, the proposed approach in analysing GBM tumours based on DTI p and q-maps images would help the clinicians to better estimate the location and size of the tumour as well as recurrence area of tumour which is not really visible to the conventional MR images. The great possibility in generating new maps using DTI and specificity using p and q maps which are complete different, would lead into better merging the isotropic and anisotropic information of the brain white tracts. The proposed augmentation of DTI-MRI improves the p and q maps segmentation. This can be improved further by combining it with conventional DTI.
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