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A FAST AND FULLY AUTOMATED APPROACH TO SEGMENT OPTIC NERVES ON MRI AND ITS APPLICATION TO RADIOSURGERY

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ABSTRACT

Delineating critical structures of the brain is required for advanced radiotherapy technologies to determine whether the dose from the proposed treatment will impair the functionality of those structures. Employing an automatic segmentation computer module in the radiation oncology treatment planning process has the potential to significantly increase the efficiency, cost-effectiveness, and, ultimately, clinical outcome of patients undergoing radiation therapy. Atlas-based segmentation has shown to be a suitable tool for the segmentation of large structures such as the brainstem or the cerebellum. However, smaller structures such as the optic nerves are more difficult to segment. In this work, we present a novel approach to automatically segment the optic nerves, which is based on Support Vector Machines (SVM). Compared to state of the art methods, the presented method obtained a better performance in regards to accuracy, robustness and processing time, being a suitable trade-off between these three factors.

Index Terms— optic nerves segmentation, machine learning, support vector machines, MRI, radiosurgery

1 Introduction

Brain tumors are the second most common cause of cancer death in men ages 20 to 39 and the fifth most common cause of cancer among women age 20 to 39 [1]. Brain tumor treatments include surgery, radiotherapy, chemotherapy, biological therapy and steroids, according to some factors, such as type, location, size or grade of the tumor. However, technological improvements in medical imaging and computing have led to increased clinical adoption of stereotactic radiosurgery (SRS) and have broadened its scope in recent years [2]. SRS aims the radiotherapy beams very precisely at the area of the brain tumour. Because SRS involves the delivery of a very high dose of radiation in either a single delivery or a small number of fractions, both the tumor and surrounding tissue must be precisely delineated.

During the SRS treatment planning, clinicians have to delineate certain organs in a huge number of images, on either Computed Tomography (CT) or Magnetic Resonance (MRI) images. Currently, this process is done manually or with very

few machine assistance. This leads to a laborious task which is, moreover, susceptible to inter- and intra-rater variability. Especially small organs, such as optic nerves (ON), are very sensitive to radiation and should therefore be avoided during the treatment. Nonetheless, these organs are notably difficult to segment.

Different techniques have been proposed over the years in the literature to (semi-) automatically segment medical images. Among them, atlas-based methods have been commonly employed to segment internal brain structures in general [3, 4] and the ON in particular [5–7]. In these approaches, a transformation is computed between a reference image volume (i.e. atlas), where the structures of interest have been previously delineated, and the target image. This transformation is then used to project labels assigned to the structures in the atlas onto the image volume to be segmented, identifying the structures of interest. Deformable registration is often used to compute such transformation [8]. Although atlas-based approaches have been reported to produce good results to segment most of the head structures from exemplar brain images, only limited success has been seen for the ON segmentation, with Dice similarity coefficients (DSC) ranging from 0.39 to 0.78, and often with long processing times.

Other approaches have also been presented to segment the ON. Bekes et al. [9] proposed a geometric based model approach to semi-automatically segment the eyeballs, lenses, ON and chiasm on CT images. Although the method was considerably fast (5-6 seconds in one CT image volume), and satisfactory quantitative results were reported for the eyeballs and lenses, qualitatively, a general lack of consistency with the results for the ON and chiasm was reported. In addition, repeatability and reproducibility of the ON and chiasm segmentation were sensitive to the positioning of seed points. Noble and Dawant [10] proposed a tubular structure localization algorithm in which a statistical model and image registration are used to incorporate a priori local intensity and shape information. Mean DSCs of 0.8 were reported when compared to manual segmentation over ten test cases. However, segmentation time for each test case was of 20 minutes.

In the presented work, a new different approach to at-

tack the problem based on machine learning techniques is proposed. First, because no required registration or alignment process is required. Second, as opposed to most of the previous works, which try to find the 3D segmentation, the presented approach relies on the segmentation of 2D single slices. Third, it provides a substantial increase of the processing time, while keeps a reasonable high similarity with respect to manual contouring. And fourth, it showed high repeatability and reproducibility.

2 Methods and Materials

The automatic pipeline process can be summarized mainly into two steps: i) 3D eyes segmentation, which result will be used as initial guess for the ON location and ii) ON slices segmentation. Once all 2D slices have been segmented, a 3D model for the ON is built and small isolated blobs are removed. The whole scheme of the proposed approach can be seen in Figure 1.

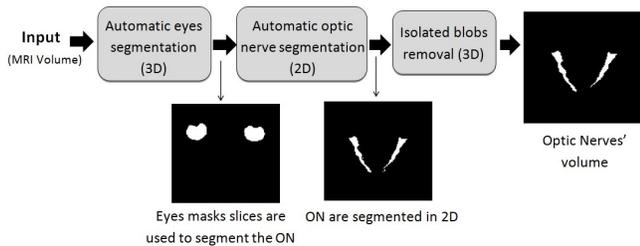


Fig. 1: Global scheme of the proposed method.

2.1 Support vector machine

Among machine learning techniques, support vector machine (SVM) represent one of the latest and most successful statistical pattern classifiers. It has received a lot of attention from the machine learning and pattern recognition community. Although SVM approaches have been mainly employed for brain tumor recognition [11] in the field of medical image classification, recent works have also used them to segment anatomical human brain structures [12, 13].

The main idea behind SVM is to find the largest margin hyperplane that separates two classes. The minimal distance from the separating hyperplane to the closest training sample is called margin. Thus, the optimal hyperplane is the one showing the maximal margin, which represents the largest separation between classes. The training samples that lie on the margin are referred as support vectors, and conceptually are the most difficult data points to classify. Therefore, support vectors define the location of the separating hyperplane, being located at the boundary of their respective classes.

The growing interest on SVM for classification problems lies in its good generalization ability and its capability to successfully classify non-linearly separable data. First, SVM attempts to maximize the separation margin i.e., hyperplane-between classes, so the generalization performance does not drop significantly even when the training data are limited.

Second, by employing kernel transformations to map the objects from their original space into a higher dimensional feature space, SVM can separate objects which are not linearly separable. Moreover, they can accurately combine many features to find the optimal hyperplane. Hence, as can be seen, SVM globally and explicitly maximize the margin while minimizing the number of wrongly classified examples, using any desired linear or non-linear hypersurface.

In the proposed work, eyes segmentation as well as ON segmentation are based on SVM. However, input features are different. While input features vector for the eyes classification case is composed by a binary mask patch, ON input features vector is composed by some other image properties, such as spatial or image texture information.

2.2 Eyes segmentation

Texture information is often sufficient to perform eyes segmentation suitably. However, if no other information is incorporated and no initial location is given, some other regions with similar texture may be considered as eyes, making sometimes necessary some kind of user interaction. Because of the well defined contrast between eyes and surrounded tissue, a different way to solve this problem is proposed, which does not require any user action. From the input MRI volume, 3D image patches of size $35 \times 35 \times 35$ are extracted in step sizes of 3 voxels over the entire volume. Region growing is applied then to this sub-volume, with the starting seed in the center of the patch. The result is a binary volume, where white voxels belong to the interest region and black voxels belong to the background (Figure 2). Voxel values from the whole $35 \times 35 \times 35$ patch are added into the input vector for the SVM classifier, leading a vector of 42875 elements.

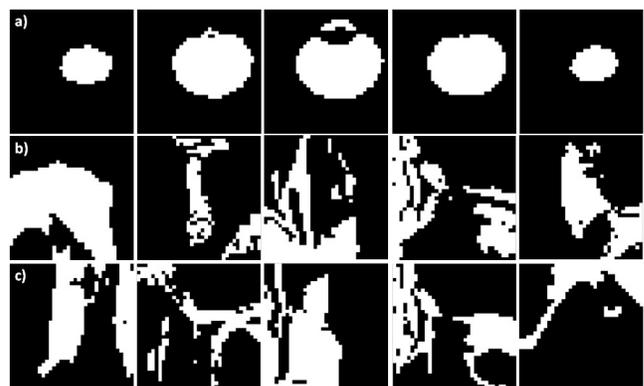


Fig. 2: Eyes binary 2D patches examples used for the training. Row a) shows 2D eyes patches while rows b) and c) show 2D non eyes patches.

Each time a 3D patch is classified as "eyes", white voxels from that patch are added into a volume, increasing the numbers of times that each voxel is labeled as "eye", and therefore creating a probability map (Figure 3). Voxels with a probability higher than 25% are then classified as eyes.

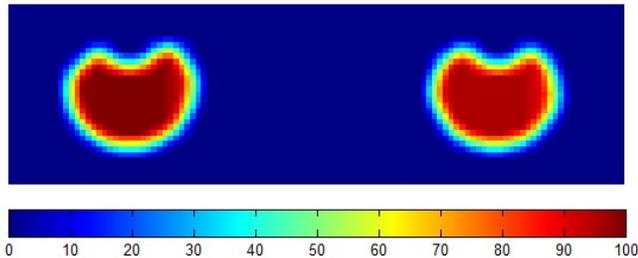


Fig. 3: Probability map created from the 3D patches classification.

2.3 Optic nerves segmentation

Image intensity information solely is not good enough for distinguishing the ON from different subcortical structures since they share similar intensity patterns in MRI. Therefore, more complex and discriminative features must be used. Different image features have been already explored to segment other subcortical structures than the ON, which can be applied to our case. The method presented in [14] used image intensity values (IIV) of the voxel and its neighborhood to be considered as input features. To provide a computationally efficient survey of the neighborhood of the voxel, signal intensity was sampled as far away as three voxels. A spherical region was also used for the 3D applications. Only voxels diagonal and orthogonal to the location of the voxel were used, which provided information from 20 and 42 surrounding voxels, respectively. Three additional nodes were used for the 3D location of the voxel. The final input feature was the frequency with which the location was found in the search space for the training set. Since their image features do not contain a shape representation, however, they needed to use a large training set. Recently, Powell et al. [12] have further developed their previous algorithm [14] using 9 IIV along with the largest gradient, a probabilistic map, and the IIVs along each of the three orthogonal axes (12 in total) instead. Additionally, 3 spherical coordinates were included, leading an input vector of 25 features in total.

Similar input vector features were used in the presented approach. Each of the ON is treated as different structure, i.e. left and right optic nerve. As in previous works, voxel probability to belong to the ON was used. Texture information was also added to the input vector. However, since the ON is a thin structure and we want to capture all texture information along it, a 7×7 patch is taken in the pixel neighbourhood, as well as gradient pixel value. Finally, spatial information is added by using the distance from the pixel to the center of the corresponding eye -*left or right* - and the angle with the horizontal line formed by the centroid of the eyes.

ON search is done in single slices and not in the entire volume. The eyes segmentation mask obtained in the previous step is used to constrain the slices where to analyze the presence of the ON.

2.4 Experiment

MR 1.5T T1-weighted brain images with voxel size of $1.0 \times 1.0 \times 1.0 \text{ mm}^3$ were used in this experiment. The proposed approach was trained using 5 subjects and tested on an independent set of 10 subjects. Automatic ON segmentations were compared to manual expert delineations by using DSC. Processing time required by the automatic method was also recorded. Since fully automatic methods are not controlled by any external factor, repeatability of such methods in the same situation is desired. For this purpose, both training and classification were performed twice with the same 5 and 10 patients, respectively, leading to serie 1 and 2. MATLAB was the platform used for this experiment. The publicly available library libsvm [15] was used for the classification task.

3 Results

Mean DSC between the automatic proposed approach and manual segmentations was 0.7624 [0.7273-0.8137] for the serie 1, and 0.7653 [0.7261-0.8207] for the serie 2. Mean automatic contouring time required by the proposed approach was 36.7 sec [20.4-45.5 sec] for the serie 1, and 35.1 sec [20.6-46.2 sec] for the serie 2. DSC and processing times for all the patients are shown in Table 1.

Patient	DSC ₁	DSC ₂	Time ₁ (sec)	Time ₂ (sec)
1	0.7938	0.7921	42.5	43.4
2	0.7424	0.7431	45.5	44.9
3	0.7937	0.799	36.9	37.1
4	0.7381	0.7444	20.4	20.6
5	0.7308	0.7352	34.8	36.1
6	0.7273	0.7261	38.2	37.8
7	0.7527	0.7517	45.1	46.2
8	0.7996	0.8030	33.2	34.1
9	0.8137	0.8207	27.1	24.9
10	0.7318	0.7379	29.4	29.3
mean	0.7624	0.7653	36.7	35.1

Table 1: Automatic segmentation performance of the proposed approach for the two segmentation series carried out.

Figure 4 shows qualitative results of the presented method to segment the ON. It can be observed that there is a high similarity between manual and automatic contours.

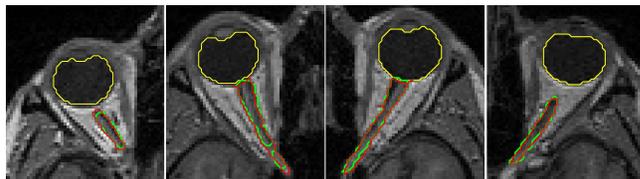


Fig. 4: ON segmentation examples. Manual segmentation are drawn in red while automatic segmentation of the proposed approach is drawn in green.

4 Discussion and conclusion

In this work, a new and fully automatic approach to segment the optic nerves on MRI has been proposed. Accu-

racy, speed and robustness of our method have been demonstrated, showing better performance compared to previously published works [5–7, 9, 10], especially when a trade-off between processing time, accuracy and robustness is taken into account. In terms of accuracy, our approach is close to the work done in [10], where mean DSC of 0.8 was reported with an overall minimum DSC of 0.74. However, the proposed method is on average 35 times faster than their approach.

Repeatability is a key factor when working with automatic segmentation methods, particularly if their introduction in clinical routine is desired. From the two segmentation series carried out in this work, it can be concluded that the proposed method is robust and repetitive, since it gives a minimal difference between two segmentations of the same patient.

To the best of our knowledge, these results suggest that the method proposed in this work is the most balanced method -in terms of accuracy, speed and robustness- to date to accomplish automatic ON segmentation. Therefore, the introduction of the proposed method in the SRS treatment planning might help physicians in the delineation task.

As future work, we aim to validate its use in clinical practice. Therefore, a further evaluation on a larger dataset and in a clinical context is envisaged. In that study, apart from similarity metrics, Dose Volume Histograms (DVH) obtained from manual and automatic segmentations will be compared. Extension of the proposed approach to other subcortical brain structures, as well as to analyze the performance of other machine learning and deep learning techniques when segmenting these subcortical structures is also planned.

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