Automatic pharynx and larynx cancer segmentation framework (PLCSF) on contrast enhanced MR images

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ABSTRACT

A novel and effective pharynx and larynx cancer segmentation framework (PLCSF) is presented for automatic base of tongue and larynx cancer segmentation from gadolinium-enhanced T1-weighted magnetic resonance images (MRI). The aim of the proposed PLCSF is to assist clinicians in radiotherapy treatment planning. The initial processing of MRI data in PLCSF includes cropping of region of interest; reduction of artefacts and detection of the throat region for the location prior. Further, modified fuzzy c-means clustering is developed to robustly separate candidate cancer pixels from other tissue types. In addition, region-based level set method is evolved to ensure spatial smoothness for the final segmentation boundary after noise removal using non-linear and morphological filtering. Validation study of PLCSF on 102 axial MRI slices demonstrate mean dice similarity coefficient of 0.79 and mean modified Hausdorff distance of 2.2 mm when compared with manual segmentations. Comparison of PLCSF with other algorithms validates the robustness of the PLCSF. Inter- and intra-variability calculations from manual segmentations suggest that PLCSF can help to reduce the human subjectivity.

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1. Introduction

In recent years, the incidence of head and neck cancer (HNC), and in particular, pharyngeal and laryngeal cancer has increased dramatically due to the influence of the human papillomavirus and other related factors [1]. Approximately 13,000 new cases for HNC with 46% of pharyngeal and laryngeal cases are reported each year in the United Kingdom with over 3300 deaths per year [1]. The definitive treatments of these types of cancer are surgery, chemotherapy and/or radiation therapy (RT) with preferred RT

treatment in an effort to preserve the organs [2]. Computed tomography (CT) has been the primary imaging modality in RT for localisation (segmentation) and staging of cancer and treatment planning with secondary information obtained from magnetic resonance imaging (MRI) and/or position emission tomography (PET). However, in recent years, dedicated MRI scanners [3] are being developed in radiation oncology to smoothly integrate MRI in RT planning (RTP) as it demonstrates excellent soft tissue characterisation, and has superior diagnostic accuracy when compared to CT [3]. Other benefits of MRI include functional imaging for tumour segmentation and dynamic imaging techniques for motion assessment, all without adding a radiation dose. Thus, localising (segmenting) the pharynx and larynx cancer from MRI for staging and treatment planning is important in spatially localised RTP. In current manual approach to segment cancer regions from axial MRI slices, radiation oncologists draw the boundary of the cancer regions. This manual segmentation process is time-consuming and subject to inter- (Fig. 1) and intra-observer variations, especially in presence of weak boundaries (Fig. 1(a)). Further, clinical work on pharynx and larynx cancer segmentation involves huge
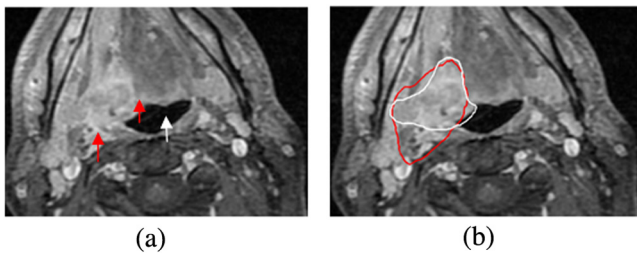
Fig. 1. (a) Original T1 + Gd (gadolinium enhanced T1-weighted) MRI slice with two red arrows to illustrate the weak and non-distinct boundary of the base of tongue cancer region, white arrow illustrate the throat region (b) Inter-variability in cancer segmentation drawn by two experts (red and white outline). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
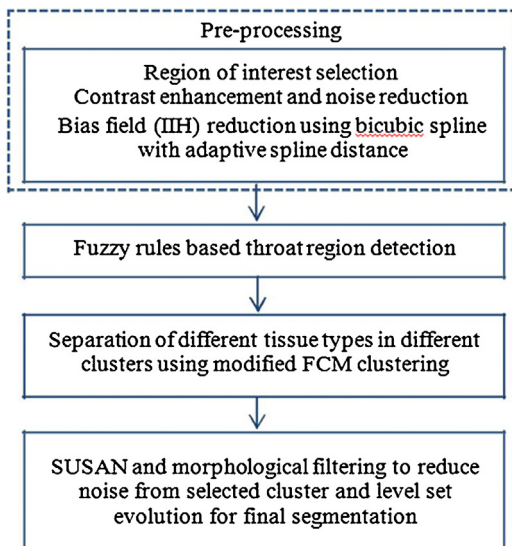

Fig. 2. Flowchart of the pharynx and larynx cancer segmentation framework (PLCSF). IIH – Intensity Inhomogeneity, FCM – Fuzzy c-means, SUSAN – Smallest Univalve Segment Assimilating Nucleus.

amount of data from different hospital centres. Thus, an automatic segmentation framework that produces quantifiable and repeatable segmentation results for the data obtained from different MRI scanners is highly desirable.

2. Related work

Many automatic and semi-automatic methods have been proposed for cancer segmentation from MRI. Some techniques [4,5] use multi-spectral MRI to segment cancer regions. However, obtaining multi-spectral MRI data is not always feasible and is expensive. Furthermore, multi-spectral MRI data may require registration step prior to segmentation due to misalignment and inconsistency. Some other techniques to segment cancer regions from single modality MRI include seed-growing [6], watershed method [7] and fuzzy connectedness [8]. These techniques do not consider spatial constraints and thus are sensitive to noise and other MRI artefacts such as intensity inhomogeneity (IIH) [9]. Further, semi-automatic approach in [6] requires manual-placing of seed points or drawing of a close loop outside the tumour from expert to segment the tongue cancer.

Active contour (AC) models [10] are also used in tumour segmentation for 2D and 3D datasets. AC is improved in [11] for concave shape brain tumours segmentation. Ho et al. [12] utilised cancer probability map as an initialisation for the evolution of a

level-set algorithm to segment blobby-shaped 3D cancer. Tongue cancer segmentation using manual initialisation for level-set is proposed in our previous work [13]. AC models, however, are sensitive to initialisation even when using 3D level set surface.

Clustering techniques, due to their robustness and efficiency, are prevalent for cancer segmentation task [14–18]. Fuzzy c-means (FCM) clustering [19] technique is modified in [14] by adding neighbourhood spatial information to correct IIH and segment brain cancer image. This technique only works with salt and pepper noise and cannot compensate for severe IIH. Prior information on cluster centres and uncertainty modelling is considered in FCM in [15] to improve FCM performance under noise and variation in data acquisition. This technique is good only if cluster centres information is known prior. FCM has been modified in our previous work [16] to segment base of tongue (BoT) cancer from magnetic resonance (MR) images. Non-parametric mean shift (MS) clustering [20] is employed in [17] as an initial step for clustering similar voxels in multidimensional feature space for breast lesion segmentation. Spectral graph clustering method notably normalised cuts (Ncut) algorithm [21] is used for cancer segmentation in [18].

In this paper we present a new pharynx and larynx cancer segmentation framework (PLCSF) for automatic segmentation of BoT and larynx (voice box) cancers from 2D (axial) contrast (gadolinium)-enhanced T1-weighted (T1 + Gd) MRI slices. The aim of this work is to assist clinicians in RTP by obtaining quantifiable and repeatable segmentation results in an unbiased manner. T1 + Gd MRI compared to unenhanced (normal) T1, proton-density and T2-weighted MRI is superior to define tumour spread for BoT and larynx cancers [22,23], as it significantly improves soft tissue contrast and cancer margin definition. However, even with T1 + Gd MRI (Fig. 1), pharynx and larynx cancer segmentation is a challenging task due to variability in its geometry, presence of necrotic tissues in the cancer region, no distinct boundaries between tumourous and healthy tissues (Fig. 1), overlap of feature values of the cancer and non-cancer pixels, and the presence of MRI artefacts. Further, significant inter- and intra- intensity variations in MRI data across patients and highly anisotropic MRI slices (maximum slice spacing 6 mm) used in this work make it reasonable to process each axial slice separately to obtain satisfactory segmentation results.

The main objective of this work is to provide the robust cancer segmentation framework (PLCSF) that integrates spatial information in an unsupervised technique without requiring the use of complex statistical modelling, atlas or the training data. The novel contributions in this PLCSF are as follows: 1) to the best of our knowledge there is no computer-aided system in the literature that is focused on the automatic segmentation of BoT and larynx cancer from T1 + Gd MRI slices; 2) the technique described in [9] is modified in this work in terms of spline distance (knot spacing) [24] parameter for bias field (IIH) estimation from a MRI slice 3) the algorithm developed for the throat region detection is novel in itself; 4) a novel technique based on FCM clustering is developed to robustly separate different tissue types in different clusters; 5) our approach does not require any manual interaction or different modalities of MRI.

The organisation of the remainder of the paper is as follows. The framework (PLCSF) developed to segment BoT and larynx cancer is presented in Section 3. Real dataset, comparison algorithms (MS clustering and NCut) and evaluation parameters used for comparison are described in Section 4. Experimental results are reported in Section 5. Finally, discussions and conclusion are presented in Section 6.