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Active learning based segmentation of Crohns disease from abdominal MRI

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ABSTRACT

This paper proposes a novel active learning (AL) framework, and combines it with semi supervised learning (SSL) for segmenting Crohns disease (CD) tissues from abdominal magnetic resonance (MR) images. Robust fully supervised learning (FSL) based classifiers require lots of labeled data of different disease severities. Obtaining such data is time consuming and requires considerable expertise. SSL methods use a few labeled samples, and leverage the information from many unlabeled samples to train an accurate classifier. AL queries labels of most informative samples and maximizes gain from the labeling effort. Our primary contribution is in designing a query strategy that combines *novel context information* with classification uncertainty and feature similarity. Combining SSL and AL gives a robust segmentation method that: (1) optimally uses few labeled samples and many unlabeled samples; and (2) requires lower training time. Experimental results show our method achieves higher segmentation accuracy than FSL methods with fewer samples and reduced training effort.

1. Introduction

Crohns disease (CD) affects the digestive tract, and can be debilitating if not detected timely [1]. Early detection can help in rapid diagnosis, reduce time and cost for therapy planning, and improve quality of life of patients. The current reference standard for CD diagnosis is colonoscopy [2] which is invasive and poses the risk of bowel perforation, thus leading to exploration of non-invasive imaging techniques to assess CD e.g., magnetic resonance imaging (MRI) [3–5], ultrasound and computed tomography (CT) [6].

In previous work we proposed a fully automatic machine learning (ML) method for detecting and segmenting CD from MRI [7,8]. The success of a robust automated system using fully supervised learning (FSL) depends upon the availability of sufficient numbers of correctly labeled samples covering a wide range of disease severities. Obtaining such data is challenging because: (1) finding qualified experts is difficult; and (2) manual annotations are time consuming. Under the above constraints we propose an active learning (AL) framework that queries the labels of *training* samples that would contribute most in designing a robust classifier. An important component of active learning systems is the query strategy to select the most “informative” sample. An excellent review of different query strategies is given in [9]. Compared to fully supervised methods our work aims to obtain higher segmentation accuracy using fewer informative samples.

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1.1. *Related work*

Analysis of colon and bowel MRI is challenging due to the complex structure of the bowel wall. Schunk in [10] analyzed MR images for their suitability in detecting inflammatory bowel disease (IBD), including CD. Tielbeek et al. in [11] compare the suitability of different imaging techniques such as MRI, DCE-MRI, and diffusion weighted imaging (DWI) for assessing Crohns disease activity. Although shape information has been widely employed for detecting abnormalities in medical images such as lymph node detection [12] and segmentation of skin lesions [13], it is unsuitable for CD segmentation because the bowel is composed of elastic tissues and does not have a rigid shape. Thus machine learning approaches are desirable in such problems.

Semi-supervised learning (SSL) [14] and active learning [9] methods have been used to overcome the limitations of insufficient labeled samples in medical applications such as segmenting anatomical structures [15] and detecting cancerous regions [16]. You et. al. [17] use self training and support vector machines (SVM) to design a semi-supervised approach for retinal vessel segmentation. Their results highlight the role of unlabeled samples in improving overall classification accuracy. Portela et al. [18] use a semi supervised clustering approach for MR brain segmentation by including prior knowledge into the clustering cost function. Tu et al. [19] propose Posterior Distribution Learning (PDL) to build a robust supervised model in data space. These works highlight the fact that user feedback on labels can improve segmentation accuracy in spite of fewer labeled samples. Part of our work is similar to online learning [20] where the classifiers are adapted incrementally using only the newly labeled samples without complete classifier retraining.

1.2. *Our contribution*

This work uses a combined SSL-AL framework for detection and segmentation of Crohns disease tissues from MR images. We compare our proposed method with our work in [7] and demonstrate that compared to fully supervised methods, combination of semi supervised and active learning achieves higher segmentation accuracy with fewer labeled samples and less training time.

Semi supervised methods learn a reliable classifier by exploiting hidden structural relationships in unlabeled data. Active learning queries the labels of ‘informative’ samples that would lead to maximum improvement in classifier performance. Although there are many well documented query strategies for active learning [9] they do not perform well for our specific problem. A preliminary version of this work appeared in [21,22] and this manuscript has the following novelties: (1) online learning is used to update the classifier after every new annotation; (2) detailed analysis of the effect of different components of the query strategy; (3) analysis on savings in training time; and (4) comparison with popular AL query strategies; Section 3 describes the image features, Sections 4–6 describe different parts of our method. We describe our dataset and results in Sections 7 and 8, and conclude with discussions in Section 9.

2. Overview of segmentation method

We validate our algorithm’s performance on manually annotated labels. Clinical experts manually segment the diseased region in every patient, and also provide labels for selected normal regions. Training of the random forest (RF) based SSL classifier starts by taking the labeled samples of the first training patient (denoted as set L). The samples from the remaining training patients are assumed to be unlabeled (denoted as set U). Note that set U consists only of the samples that have been annotated by the experts, and does not comprise of all voxels of the image. The AL part selects the most informative sample in U whose label is obtained from the stored label set. This sample is added to set L and the classifier is updated using online learning. The query continues till the query selection algorithm cannot identify a novel informative sample, i.e., a sample whose characteristics have not been added to the training set L.

Since classifying each voxel in a 3D volume is time consuming, we make use of a volume of interest (VOI) enclosing the bowel tissues. Our algorithm analyses each VOI voxel to generate a classification map whose negative log-likelihood is the penalty cost in a second order Markov Random Field (MRF) cost function. Graph cuts (GC) is used to optimize this function and segment the diseased region. The VOIs are obtained from our previous method in [7]. An overview of our method is given in Algorithm 1.

Algorithm 1. Semi supervised and active learning for segmenting Crohn’s Disease tissues

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Input Image with ‘diseased’ VOI obtained from [7].
Output Segmented diseased region.
Sequence of steps:
(1) Bias correction and intensity normalization.
(2) Train $RF-SSL$ classifier with labeled samples of the first training patient (set L) and unlabeled samples of remaining training patients set U.
(3) Determine the most informative sample from U and query its label.
(4) Add labeled sample to L and update $RF-SSL$ using online learning.
(5) Continue label query till no further queries are required. This completes training of $RF-SSL$.
(6) For test patient generate classification map for the VOI patches using the final $RF-SSL$.
(7) Segment diseased regions using final classification map and graph cuts (Eqs. (11) and (12)) to give the diseased bowel tissue.

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3. Image features

The images are first bias-corrected using the method in [23] to remove intensity inhomogeneities due to the magnetic field of MR machines. Other intensity inhomogeneity correction methods such as in [24,25] perform equally well for our data. Pixels with the lowest 5% intensities usually indicate noise,