Neurocomputing 204 (2016) 125–134

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Medical media analytics via ranking and big learning: A multi-modality image-based disease severity prediction study

Wei Huang [a,*], Shuru Zeng [a], Min Wan [a], Guang Chen [b]

[a] School of Information Engineering, Nanchang University, Nanchang, China
[b] Xian Communications Institute, Xian, China

ARTICLE INFO

Article history:
Received 28 February 2015
Received in revised form
14 June 2015
Accepted 9 July 2015
Available online 9 April 2016

Keywords:
Medical media analytics
Disease severity prediction
Learning
Ranking

ABSTRACT

Medical media analytics receives vast popularity nowadays because of its effectiveness in improving the performance of diverse health-care applications. In this study, the essential disease severity prediction problem in medical media analytics is investigated and a computer-aided diagnosis (CAD) strategy based on ranking and learning techniques is presented to tackle the disease severity prediction task. To be specific, two types of magnetic resonance images (MRI), including T1-weighted images as anatomic MRI and arterial spin labeling (ASL) images as functional MRI, are incorporated as multi-modality images to provide image-based information for dementia disease severity prediction in this study. There are two main steps composed of the whole CAD strategy. First, the problem of partial volume effects (PVE) mainly caused by signal cross-contamination due to pixel heterogeneity and limited spatial resolution of ASL is focused. Conventional regression-based PVE correction methods are discussed and their inherent problems of blurring and brain details loss in correction results, which prevents the actual brain atrophy being revealed, are studied. A pixel-based PVE correction method, which only counts on single pixel information and formulates the PVE correction problem as a constrained optimization problem solved via the split-Bregman algorithm, is presented to solve the problem. Second, ranking and learning techniques are incorporated based on multi-modality images after performing PVE correction for dementia disease severity prediction. Technically, a conventional discrete position-based ranking evaluation measure is approximated and its surrogated continuous form is optimized via gradient ascend for ranking functions learning. A large database composed of multi-modality images acquired from 320 real patients is utilized for experimental evaluation. Extensive experiments and comprehensive statistical analysis are carried out to demonstrate the superiority of the introduced CAD strategy with comparison to several existing ones. Promising results are reported from the statistical perspective.

1. Introduction

It is widely acknowledged that social media analytics receives vast popularity nowadays because of its latent capability of measuring, analyzing, interpreting diverse interactions and associations between a large group of populations, as well as its powerful capacity in uncovering and predicting individuals sentiment [1]. Medical social media analytics, on the other hand, specializes in health-care utilizations and is particularly beneficial for patients' disease prediction and diagnosis, with the help of diverse types of information (e.g., either text-based or image-based) as well as big learning techniques (e.g., deep learning and ranking). In this study, the essential disease prediction problem in medical social medial analytics is focused. Novel ranking and learning techniques are introduced and incorporated for Alzheimer's Disease (AD) prediction based on multi-modality image-based information.

AD, the most common form of dementia disease, is often diagnosed in patients over 60 years old, and generally regarded as one of the five most serious non-communicable diseases (i.e. others include cardiovascular disease, cancer, diabetes and chronic lung disease) in the whole world reported by the World Health Organization [2]. According to a population-based study conducted by the United Nations, there are already over 26.6 million AD patients diagnosed globally [3], and 1 in 85 people all around the world is predicted to be suffering from AD by the year 2050 [4]. In China, the number of AD patients is believed to exceed 10 million. Accurate diagnosis and timely treatment is essential to delay the onset and progression of AD [4], and it can be realized in medical social media analytics with the help of ranking and learning techniques.

In order to diagnose the progression of dementia disease accurately, various medical imaging modalities have been

* Corresponding author.

http://dx.doi.org/10.1016/j.neucom.2015.07.148
0925-2312/

investigated and utilized. Among them, Magnetic Resonance Imaging (MRI) is a powerful imaging tool and receives vast popularity because it is free of radiation exposure, compared with other conventional imaging tools such as Computed Tomography (CT) and Positron Emission Tomography (PET), for patients safety issues. For MRI, a variety of imaging techniques are proposed in the last decades, and many of them can be categorized into two types, anatomical MRI (aMRI) and functional MRI (fMRI) [5]. It is commonly seen for aMRI to be utilized in both clinical diagnosis and academic research for obtaining the anatomy of scanned patients, while fMRI receives more and more research interests nowadays by providing extra information about scanned patients, which may become obscure in aMRI, through detecting associated changes in blood flow of scanned patients [5]. Arterial Spin Labeling (ASL), which is an emerging fMRI technique, receives increasing attention in dementia diagnosis studies recently [6]. Compared with other conventional fMRI techniques, such as Blood Oxygen Level Dependent (BOLD), ASL requires no injection of external contrast enhancement agent (e.g., gadolinium) into patients while being scanned. Thus, unfavored anaphylactoid reactions on patients [7] can be totally avoided in ASL images, making it absolutely safe and more favored for dementia diagnosis at present.

Technically, an ASL image is produced by two types of images: a label image and a control image. Their acquisition steps are illustrated in Fig. 1. The yellow region 2 in Fig. 1a and the green region 4 in Fig. 1b describe the same Region-of-Interest (ROI), in which ASL images are acquired. The purple region 1 in Fig. 1a represents an area where arterial blood water is magnetically labeled via a 180° Radio-Frequency (RF) inversion pulse. In this way, water molecules within the arterial blood are magnetically labeled and utilized as the "tracer", instead of the conventional injected contrast enhancement agent mentioned above. Label images are taken when labeled blood water flows into the ROI, and example label images from the transverse view acquired from one patient in this study are displayed in Fig. 1a. For control images, the blood water is not magnetically labeled, and control images are taken at the same ROI directly. Example control images of the same patient are displayed in Fig. 1b. Although label and control images look similar towards each other, certain differences exist between them and an ASL image is produced as their difference (i.e., using a control image minus a corresponding label image) therein, and example ASL of the same patient is illustrated in Fig. 1c. Generally speaking, the Cerebral Blood Flow (CBF) on each pixel of ASL is proportional towards its ASL signal, and brain atrophy within particular brain regions of demented patients can be revealed by low measured

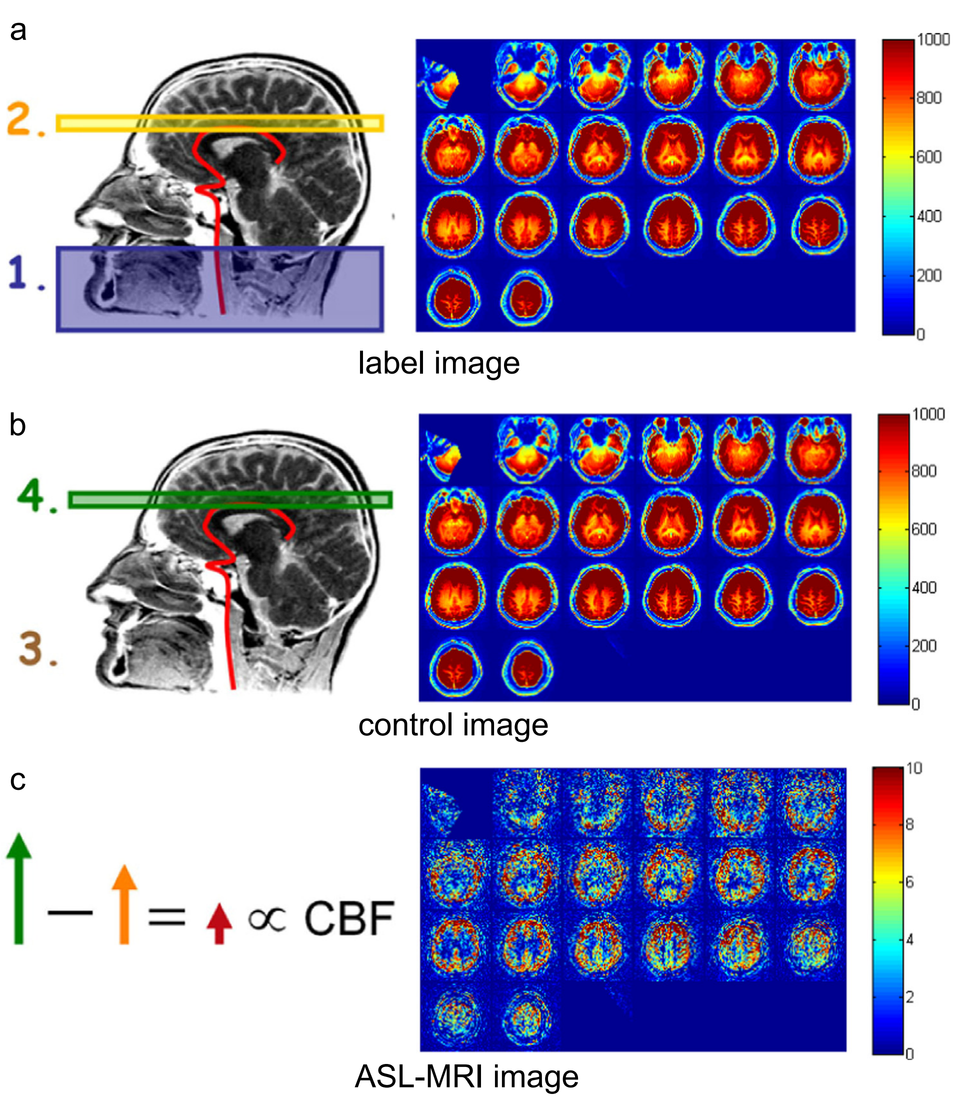

Fig. 1. An illustration of ASL acquisition with example images displayed from the transverse view (the plotting scale unit is [mL/(100 g min)]). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)