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Editorial

Impact of advanced parallel or cloud computing technologies for image guided diagnosis and therapy

Kelvin K.L. Wong[a,*], Simon Fong[b] and Defeng Wang[c]
[a]*School of Medicine, Western Sydney University, Sydney, Australia*
[b]*Department of Computer and Information Science, University of Macau, Taipa, Macau SAR, Macau, China*
[c]*Department of Imaging and Interventional Radiology, Research Center for Medical Image Computing, The Chinese University of Hong Kong, Hong Kong*

Medical imaging technology has revolutionized health care for a long time. The past decade has witnessed considerable advancements in imaging techniques, developing from structural to functional or from static to dynamic, which enabled both individual- and population-based analysis. While the number of multimodality imaging-based diagnoses and procedures is increasing considerably, effective, safe, and high speed/quality imaging is important for much medical decision-making. However, it's impossible to realize these standards free from powerful computing technologies. Image processing with graphics processing unit (GPU)-based parallel computing technique is an alternative way to solve image processing problems in multimodality image diagnoses and telemedicine, which require large times of processing as well as handling large amounts of information in "acceptable time". Cloud computing has been introduced only recently but is already one of the major topics of discussion in research and clinical settings. The provision of extensive, easily accessible, and reconfigurable resources such as virtual systems, platforms, and applications with low service cost has caught the attention of many researchers and clinicians. However, it is still in its infancy in the medical imaging domain, and there is currently low market penetration within the field. This situation may change rapidly in the near future. Among the potential driving forces for the increased use of cloud computing in medical imaging are raw data management and image processing and sharing demands, all of which require high-capacity data storage and computing. With the development of high speed/quality imaging technologies, medical imaging societies have to embrace parallel and/or cloud computing technologies and use them as a powerful tool to enhance the efficiency and accuracy of multimodality imaging data analysis.

In this special issue, we invite the latest research works from both academia and practitioners to share experiences and ideas on how best we could make use of advanced parallel or cloud computing

*Corresponding author: Kelvin Kian Loong Wong, School of Medicine, Building 30, Western Sydney University Campbelltown Campus, Narellan Rd & Gilchrist Dr, Campbelltown NSW 2560, Australia. Tel.: +61 4620 3620; E-mail: kelvin.wong@westernsydney.edu.au.

technologies and turn them into clinical applications for image-guided diagnosis and therapy. All technological solutions from all level collectively contribute to one purpose which is better health for everyone. Thus, this special issue focuses on the applications for problems in the cloud domain, covering the solution for special problems or finding the potential correlation between diseases and some factors that seem unrelated. The main goal of this special issue is to provide the overview of the current state-of-the-art advances in the process of medical diagnosis. The issue has 10 research articles dealing with a range of problems related to machine learning and data mining methods (e.g., classification, clustering) and their applications, and the integration methods of multi-modal neuroimaging data and their applications. Details of these papers are as follows.

The first two articles dealt with visualization of anatomy and their examination using medical imaging technology. The first one by Chai et al. [1] proposed a novel real-time monitoring system with accelerator using the magic finger based on binocular location and support vector machine (SVM). The system consists of three parts: a binocular system, a software which monitors the patient positioning in real-time, and a magic finger to control the treatment bed. For the binocular system, the paper proposed a novel and an efficient calibration-reconstruction method [2]. To reduce the computation for the real-time monitoring, this study applied the epipolar geometry [3] for the left and right images matching. At last, this study used the SVM to classify the monitoring results, and judged whether to control the treatment bed as the monitoring results. This work is rather practical in radiotherapy monitoring field and provides a new perspective for the precise radiotherapy.

The second article dealt with the diagnostic performance of magnetic resonance imaging (MRI) was contributed by Peng et al. [4]. They proposed an analysis to compare the value of MRI with clinical examination in staging of uterus cervical carcinoma (UCC), which remains the second most commonly diagnosed cancer among female patients and the effective approaches towards UCC rely heavily on the precise pre-surgical staging [5–8]. The conventional International Federation of Gynecology and Obstetrics (FIGO) system based on clinical examination is being applied worldwide for UCC staging. Yet, its performance just appears passable. The study results suggested that MRI had relatively high accuracy in evaluating UCC staging when compared with current clinical examination method based on FIGO.

The third and fourth articles investigated the feasibility of applying parallel computing to facilitate the use of computational fluid dynamics (CFD) and smooth particle hydrodynamics (SPH) in modelling blood flow. One article by Qin et al. [9] presented a robust method for comparison of arterial flow velocity contours by SPH with the well-established CFD technique in computed tomography (CT) reconstructed arteries. Stenosis in arteries is the result of atherosclerosis, and is one of the most common cardiovascular problem that can lead to the malfunction of the vascular system [10–12]. The authors based their study on three-dimensional (3D) straight and curved arterial models of millimeter range with a 25% stenosis in the middle section. In addition, they studied the influence of particles number on SPH versus CFD deviation for blood flow velocity distribution. Experiments showed that, the SPH method had a big potential to be used in the virtual surgery system, such as to simulate the interaction between blood flow and the CT reconstructed vessels. Especially, those with stenosis or plaque when encountering vasculopathy, and for employing the simulation results output in clinical surgical procedures.

The article by Ko et al. [13] investigated pulsatile hemodynamics changes throughout a cardiac cycle in a Stanford Type B thoracic aortic dissection (TAD) model with the aid of CFD method. Clinically, aortic dissection (AD) is one of the most catastrophic and non-traumatic cardiovascular diseases and has a fatality rate of up to 90% when left untreated [14–16]. A patient-specific dissected aorta geometry was reconstructed from the 3D computed tomography angiography (CTA) scanning. The realistic time-dependent pulsatile boundary conditions were prescribed for the 3D patient-specific TAD model. The aortic wall was assumed to be rigid, and a no-slip boundary condition was applied at the wall while the CFD simulations were processed using the finite volume (FV) method to investigate the pulsatile hemodynamics in terms of blood flow velocity, aortic wall pressure, wall shear stress and flow vorticity. Their experiments indicated that, a high wall shear stress and strong vertical flow was observed at dissection initiation. In addition, wall shear progressed along the false lumen, which was a possible cause of blood flow between aortic wall layers. This could provide complementary information to clinicians for better understanding of the pulsatile hemodynamics and help in designing a diagnostic tool for patients with TAD.

The fifth and sixth articles focused on the study of neurology. The article by Cai et al. [17] focused on imaging application in diagnostic evaluation of the medical condition related to neurological diseases and neuroimaging. A precise lesion lateralization and neurosurgery decision-making is important in intractable epilepsy patients. Since epilepsy affects more than 65 million people worldwide, a third of whom have seizures that are resistant to anti-epileptic medications. A large proportion of these intractable patients may be amenable to surgical therapy or treatment with implantable devices under the image guidance with advances in neuroimaging and cloud computing. This has been shown to be of great help in some blastoma patients [18]. And also been shown to applicable in general epilepsy patients [19]. What's more, specifically, image guidance diagnosis has been used in frontal lobe epilepsy patients [20]. However, image guidance has never been used in a more refined and crucial areas such as the supplementary sensorimotor area (SSMA). A problem of great concern is how to provide a reliable definite lesion lateralization marker for epilepsy patients involved in supplementary sensorimotor area (SSMA). By using the combined application of image guidance diagnosis and neurophysiology (electro-semiology), the authors focused their investigation target only on the restricted epileptogenic lesions limited to pure SSMA (confirmed by comparative operative MRI and long-term follow up). Study results showed that unilateral extension and abduction posturing in upper limb was the most prominent and valuable sign for the lesion lateralization in SSMA epilepsy patients' neurosurgery decision-making. Thus, the study finding suggested that image guidance diagnosis (comparative pre- and post- operative MR images) and combined using of other modalities (such as electro-semiology) can be of great diagnostic value in the evaluation of the medical conditions related to some refractory neurological cases.

The article by Zhang et al. [21] dealt with epileptic seizure detection in electroencephalogram (EEG). As we know, epilepsy is a chronic disease, whereby the neurons in the brain discharge suddenly, and causing the brain to have a short dysfunction [22] which may result in cognitive decline, convulsion, injury or even death [23]. This article presented a method for automatic epileptic seizure detection in EEGs based on multi-fractal detrended fluctuation analysis (MF-DFA) and support vector machine (SVM). MF-DFA is a great way to extract features for analysing EEG because of its simple algorithm procedure and less parameters. The study tested the method using a public dataset [24] and the results showed that the new feature extraction method could describe signals with less features and the accuracy of the classification reached up to 99%. Thus, the classification model could achieve comparable accuracy, which means that it is effective in epileptic seizure detection.

The seventh and eighth articles reported the studies that applied a similar technology to Surface electromyography (sEMG) to improve feature extraction and classification based on parallel computing. The article by Luo et al. [25] proposed a genetic algorithm (GA) based Multi-layer Perception (MLP) multi-classification method using GPU acceleration to classify sEMG signals which can be used in the medical prosthetic field. Since traditional EMG is unstable and nonlinear, more attention has been turned to feature extraction and classification of sEMG [26, 27]. In order to select representative features from candidate features, this study used GA which could effectively optimize feature selection to reduce the number of features and the use of GA enabled less features to represent samples. In addition, the study used the trained MLP [28] classifier to predict the classes of sEMG signals. Experimental results showed that the model has higher accuracy and the feature optimization method was more effective as comparing to other existing methods. In addition, it could have practical application value in medical prosthetics and the potential to improve robustness of myoelectric pattern recognition.

The article by Wen et al. [29] presented research on the sEMG signals that are produced by clicking mouse buttons. The sEMG is often used for diagnosing patients with neuromuscular disorders [30]. The proposed method included four steps: data acquisition, sample extraction, feature extraction, and classification. In sample extraction section, a window-based data acquisition method was applied to extract signal samples from sEMG electrodes. In feature extraction step, a 2-dimensional matrix image based feature extraction method was proposed, which is different from classical methods and could transform samples to feature maps for classification. Finally, classical classification algorithms (SVM, KNN, RBF-NN) [31–33] were employed to classify these feature maps. The authors identified that, all these classifiers can classify sEMG samples effectively, and the accuracy of the SVM classifier could reach up to 100%.

The ninth article contributed by Lok et al. [34] presented research on the fast and robust brain tumor segmentation. Brain tumor is a collection of mass of abnormal cell which can be subdivided into active tumor region, necrosis region and edema [35]. Multiple medical images are required to delineate brain tumor accurately due to its heterogeneous content and intensity [36]. This study presented a novel level set method by combining region information of multiple images. A signed pressure force function based on the global statistical information of grey intensity in multiple images was used to replace the edge stopping function in the traditional geodesic active contour model [37]. In addition, a new metric model related to the direction and velocity of the contour evolution named direction term was defined for controlling the segmentation of specific tumor region, such as active tumor region or necrosis region. The new method was evaluated with clinical data by quantitative measurement. Study results demonstrated the effectiveness and robustness on segmenting homogeneously-enhanced tumor, heterogeneously-enhanced tumor, ring-enhanced tumor and non-enhanced tumor with a 2D user-defined initial contour.

Finally, the last article by Feng et al. [38] presented a three-dimensional echocardiography (3DE), which provides an important clinical assessment of left ventricular volume. Currently, data processing of traditional quantitative method requires cumbersome manual adjustment, which is time-consuming and of highly operator-dependency, which make it difficult to be widely used in the clinical practice [39, 40]. Heart Model (HM) is a newly developed automatic left ventricular volume adaptive quantitative software based on big data, which is simple and rapid for quantifying left ventricular volume and function [41]. This study evaluated the feasibility and reproducibility of HM in assessing left ventricular volume and function in patients with left atrial and left ventricular remodeling, Comparing to the traditional quantitative method, the study demonstrated that HM was feasible, required minimal analysis training and was highly reproducible and timesaving. Thus, it promises to facilitate the integration of 3D-based left-heart chamber quantification into clinical practice.

In summary, these 10 selected articles contributed by researchers with a wealth of knowledge in different neurology research and neuroimaging research fields provide readers with valuable sources of information on the recent progress in medical informatics. We hope this special issue will provide a platform for researchers, clinicians, and healthcare professionals to collaborate on some research areas with the aim of promoting medical scientific study. Also, it can be used as a valuable source of references for researchers to conduct more advanced studies in this field.

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