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Editorial Learning for Medical Imaging

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Editorial

Learning for Medical Imaging

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Medical imaging is the technique of creating visual representations of the interior of a body for clinical analysis and medical intervention. As a multidisciplinary field, medical imaging requires the improvements in both science and engineering to implement and maintain its noninvasive feature. Since single-sample evidence obtained from the patient's imaging data is always not sufficient to provide satisfactory performance, learning from examples or subjects to simulate physician's prior knowledge of medical imaging data is highly demanded in medical imaging field. Machine learning, aiming at learning from examples/data for prediction, classification, regression, and identification, has been routinely performed in medical image analysis in the last decade. With advances in medical imaging, new imaging modalities and methodologies, such as cone-beam/multi-slice Computed Tomography (CT), 3D/4D ultrasound, diffusion-weighted Magnetic Resonance Imaging (MRI), electrical impedance tomography, and diffuse optical tomography, generate more complex imaging data than before. To address these issues, devising advanced machine learning and statistical techniques is indispensable in medical imaging fields, such as computer-aided diagnosis, image fusion, image segmentation, image registration, image-guided therapy, and image retrieval.

The main aim of this special issue is to bridge the gap between machine learning techniques and their applications in medical imaging data. Specifically, this special issue targeted the most recent technical progresses on learning techniques for medical imaging data, including classification [1, 4, 6, 9, 20, 24], clustering/segmentation [2, 19], feature selection [13, 18, 25], genetic algorithm [23], and many others, in many kinds of learning-based applications, including microscopy image sequences [1], dementia diagnosis [3, 7, 10, 14, 15], medical image denoising [5, 8], medical ultrasound images [11], electroencephalogram data analysis [12], omni-directional m-mode echocardiography system [16], medical image registration [17, 22], ultrasound imaging analysis [21], and so on.

The topics of the special issue are interesting, so in total, this special issue have received 51 submissions from at least 30 different research departments over the world. After at least two rounds of reviews, we finally accepted 25 papers for publication. We summarize the introduction of accepted papers as follows:

The paper by Hao *et al.* [1] proposed a mitotic cell recognition method by integrating heterogenous data into the frame-

work of cross domain learning, to solve the challenging of accurate and automatic identification of mitosis in all kinds of biomedical applications. First, the proposed method extracted discriminative features to represent the local structure and textural saliency of individual cell sample. Second, the cell type-dependent classifiers were respectively trained on the target domain and the auxiliary domain, which were then fused in the framework of adaptive Support Vector Machine (SVM) for conducting cross-domain learning. The resulting classifier could be implemented for mitotic cell recognition in the cross domain manner, while the proposed framework could reduce the requirement on large-scale manual annotation on the target domain, by implicitly augmenting the training data with the existing annotated auxiliary. The extensive experiments on two kinds of phase contrast microscopy image sequences (*e.g.*, C3H10T1/2 and C2C12) showed that the proposed method enabled to leverage the datasets from multiple domains to boost the performance by effectively transferring the knowledge from the auxiliary domain to the target domain.

The paper by Peng *et al.* [2] studied the issue of image segmentation, especially for object(s)-of-interest since designing an efficient and robust object(s)-of-interest segmentation method is challenging in either computer science or applied mathematics. To do this, the authors proposed an object(s)-of-interest segmentation method for images with inhomogeneous intensities. Specifically, this paper first introduced a discrimination function to label each pixel of images, for determining whether the pixel belonged to the object(s)-of-interest based on the characteristics of object(s)-of-interest. The resulting objective function was then integrated with image gradient to define a stopping function and form an energy function. Finally, the energy function was minimized by means of an existing level set evolution method to guide the motion of the zero level set toward object boundaries. The experimental results demonstrated that the proposed model was effective, compared to the state-of-the-art methods.

The paper by Zhu *et al.* [3] proposed a graph feature selection method for dementia diagnosis, *i.e.*, Alzheimer's Disease (AD) diagnosis, by considering the information inherent in the observations into the framework of sparse multi-task learning. Specifically, this paper first defined two relations (*i.e.*, the feature-feature relation and the sample-sample relation, respectively) based on prior knowledge of the data. The feature-feature selection enforced the similarity relationship between

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