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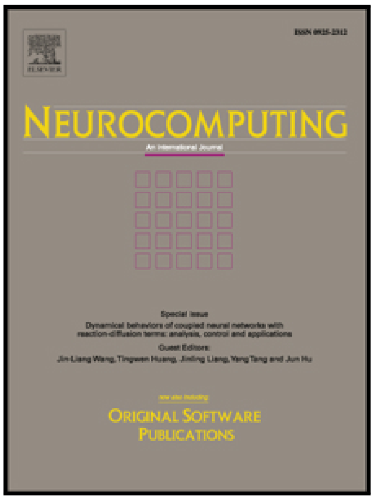

Editorial: Deep Learning for Medical Image Analysis

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Editorial: Deep Learning for Medical Image Analysis

This special issue collects the original contribution of works which addresses the challenges from the deep learning techniques for medical image analysis. Papers on pure medical imaging would be out of the scope of this special issue. This special issue received 104 submissions. After a full reviewing process involving more than two qualified reviewers for each paper and at least two rounds of revision, we selected 20 papers for publication. All of those papers represent a sample of the current advances on deep learning techniques for medical image analysis.

The papers are organized as follows:

In the first paper this special issue “Convolutional Neural Network Based Diagnosis of Bone Pathologies of Proximal Humerus”, Aysun Sezer et al. introduce an innovative representation of a learning framework for diagnosis of bone lesions from PD MRI sequences that integrates deep learning techniques to automatically learn discriminative features while avoiding the design of specific hand-crafted image-based feature descriptors. The automatically segmented PD weighted shoulder images were evaluated by the proposed convolutional neural network (CNN) to extract features and classify humeral head in three groups as normal, edematous and Hill-Sachs lesion with a success rate of %98.43.

In paper “Deep Learning for Ultrasound Image Caption Generation based on Object Detection”, Xianhua Zeng et al. propose a novel method of ultrasound image captioning generation based on region detection. The method simultaneously detects and encodes the focus areas in ultrasound images, then utilizes the LSTM to decode the encoding vectors and generate annotation text information to describe the diseases content information in ultrasound images.

The paper “Non-contact Heart Rate Detection under Non-cooperative Face Shake”, Hongwei Yue et al. propose a video-based face-shake-resistant heart rate detection method to extract the blood volume pulse signal. Firstly, the face region selected through multi-task convolution neural networks was corrected the tilt angle to obtain the face image sequence, and the face image sequence has the same skin color information with approximate. Then, the empirical mode decomposition and the permutation entropy were combined, and the initial position of the signal was determined according to the randomness of the intrinsic mode function component to denoise and reconstruct the blood volume pulse signal. Finally, the spectral analysis was implemented for the reconstructed signal to compute the heart rate value.

In the paper “Heart Sounds Classification Using a Novel 1-D Convolutional Neural Network with Extremely Low Parameter Consumption”, Bin Xiao et al. propose a novel heart sound classification method based on deep learning technologies for cardiovascular disease prediction. This work is mainly comprised three parts: pre-processing, 1-D waveform heart sound patches classification using a deep convolutional neural network (CNN) with attention mechanism, and majority voting for final prediction of heart sound recordings. In order to enhance the information flow of the CNNs, a block-stacked style architecture with clique blocks is employed, and in each clique block a bidirectional connection structure is introduced in the proposed CNN. By using the stacked clique and transition blocks, the proposed CNN achieves both spatial and channel attention leading a promising classification performance.

Moreover, a novel separable convolution with inverted bottleneck is utilized to decouple the spatial and channel-wise relevancy of features efficiently.

In “Dynamic MRI Reconstruction Exploiting Blind Compressed Sensing Combined Transform Learning Regularization”, Ning He et al. focus on blind compressed sensing (BCS), where the underlying sparse signal model is a priori unknown, and propose a framework to simultaneously reconstruct the underlying image as well as the unknown model from highly under-sampled measurements. Specifically, in this model, the patches of the under-sampled images are approximately sparse in a transform domain. Transform learning that combines wavelet and gradient sparsity is considered as regularization in this model for dynamic MR images. The original complex problem is decomposed into several simpler subproblems, then each of the subproblems is efficiently solved with a variable splitting iterative scheme.

In the paper “Multi-label Transfer Learning for the Early Diagnosis of Breast Cancer”, Hiba CHOUGRAD et al. propose the joint learning of the tasks using multi-label image classification. Furthermore, this work introduces a new fine-tuning strategy for using transfer learning, that takes advantage of the end-to-end image representation learning when adapting the pre-trained Convolutional Neural Network (CNN) to the new task. This work also proposes a customized label decision scheme, adapted to this problem, which estimates the optimal confidence for each visual concept.

In “Automated hepatobiliary toxicity prediction after liver stereotactic body radiation therapy with deep learning-based portal vein segmentation”, Bulat Ibragimov et al. propose a novel framework for automated HB toxicity prediction by combining deep learning-based auto-segmentation, PV anatomy analysis and the previously reported HB toxicity model. For validation of the framework, an IBR approved representative database of 72 patients treated with SBRT from primary (37) and metastatic (35) liver cancer was assembled. Each case included a pre-treatment CT, manual segmentations of tumor and PV, approved treatment plan, and the record of acute and late post-treatment toxicities.

In the contribution “Robust Brain Extraction Tool for CT Head Images”, Zeynettin Akkus et al. present a robust method based on fully convolutional neural networks (CNN) to remove non-brain tissues from head CT scans in a computationally efficient manner. The method includes an encoding part, which has sequential convolutional filters that produce feature representation of the input image in low dimensional space, and a decoding part, which consists of convolutional filters that reconstruct the input image from the reduced representation.

In the paper “A Fully Convolutional Network Feature Descriptor: Application to Left Ventricle Motion Estimation Based on Graph Matching in Short-Axis MRI”, Junhao Wu et al. train a fully convolutional network to predicate endocardial contours and extract features of points from short-axis cine MRI. A LV graph is constructed using the extracted point features, and a convex graph matching cost function is defined to estimate the point correspondence between images at two given phases. The sparse and double stochastic constraints are introduced into the cost function, which is optimized by the alternating direction method of multipliers (ADMM) iteratively. Finally, the transformation using compact supported radial basis functions with sparse constraint is employed to estimate the dense displacement defined between two cardiac images at two phases based on the corresponding relationship.

In “Super-resolution Reconstruction of Single Anisotropic 3D MR Images Using Residual Convolutional Neural Network”, Jinglong Du et al. present a novel CNN-based anisotropic MR image reconstruction method based on residual learning with long and short skip connections. The proposed network can effectively alleviate the vanishing gradient problem of deep networks and learn to restore high-frequency details of MR images. To reduce computational complexity and memory usage, the proposed network utilizes cross-plane self-similarity of 3D T1-weighted (T1w) MR images.

In “A Framework for Hierarchical Division of Retinal Vascular Networks”, Linfang Yu et al. recommend an executable framework for the hierarchical division of the retinal vascular networks. Specifically, a supervised method based on deep neural network is used for retinal blood vessel segmentation. A graph-based method is also applied to generate vascular trees from the segmented retinal vessels. This work presents two algorithms: the potential landmark detection algorithm (PLDA) is used to identify the bifurcations and crossings; and the adaptive hierarchical classification algorithm (AHCA) is used in the hierarchical characteristics classification of vascular bifurcations.

In the paper “Analysis of Tuberculosis Severity Levels from CT Pulmonary Images Based on Enhanced Residual Deep Learning Architecture”, Xiaohong Gao et al. investigate the application of CT pulmonary images to the detection and characterization of TB at five levels of severity, in order to monitor the efficacy of treatment. To contend with smaller datasets (i.e.

in hundreds) and the characteristics of CT TB images in which abnormalities occupy only limited regions, a 3D block-based residual deep learning network (ResNet) coupled with injection of depth information (depth-Resnet) at each layer was implemented.

In the paper “Lung Adenocarcinoma Diagnosis in One Stage”, Pengyi Hao et al. construct a one-stage framework relying on feature pyramid network (FPN) for the diagnosis of lung adenocarcinoma (LA). The proposed network has two advantages, i) it can localize and classify LAs simultaneously. ii) it generates feature maps with high resolution, from which robust classification is reached since tight coverage takes less contextual information.

In “Fine-tuning Pre-trained Convolutional Neural Networks for Gastric Precancerous Disease Classification on Magnification Narrow-band Imaging Images”, Xiaoqi Liu et al. propose a transfer learning framework by fine-tuning pretrained convolutional neural networks (CNNs) to classify gastric M-NBI images into three classes: chronic gastritis (CGT), low grade neoplasia (LGN) and early gastric cancer (EGC). Results show that the performance of fine-tuned CNNs outperforms traditional handcraft features and trained CNNs.

In “CcNet: A Cross-connected Convolutional Network for Segmenting Retinal Vessels Using Multi-scale Features”, Shouting Feng et al. propose a cross-connected convolutional neural network (CcNet) for the automatic segmentation of retinal vessel trees. In the CcNet, convolutional layers extract the features and predict the pixel classes according to those learned features. The CcNet is trained and tested with full green channel images directly. The cross connections between primary path and secondary path fuse the multi-level features.

In the paper “Deep Learning for Variational Multimodality Tumor Segmentation in PET/CT”, Laquan Li propose a novel deep learning based variational method to automatically fuse multimodality information for tumor segmentation in PET/CT. A 3D fully convolutional network (FCN) was first designed and trained to produce a probability map from the CT image. The learnt probability map describes the probability of each CT voxel belonging to the tumor or the background, and roughly distinguishes the tumor from its surrounding soft tissues. A fuzzy variational model was then proposed to incorporate the probability map and the PET intensity image for an accurate multimodality tumor segmentation, where the probability map acted as a membership degree prior. A split Bregman algorithm was used to minimize the variational model.

In the paper “Computer Aided Alzheimer's Disease Diagnosis by An Unsupervised Deep Learning Technology”, Xiuli Bi et al. propose a fully unsupervised deep learning technology for AD diagnosis. This work first uses the unsupervised Convolutional Neural Networks (CNNs) for feature extraction, and then utilize the unsupervised predictor to achieve the final diagnosis. In the proposed method, two kinds of data forms, one slice and three orthogonal panels (TOP) of MRI image, are employed as the input data respectively.

In “Brain tumor segmentation with Deep Convolutional Symmetric Neural Network”, Hao Chen et al. propose a novel deep convolutional neural network which combines symmetry to automatically segment brain tumors. The proposed Deep Convolutional Symmetric Neural Network (DCSNN), extends DCNN based segmentation networks by adding symmetric masks in several layers.

In the contribution “Bin loss for hard exudates segmentation in fundus images”, Song Guo et al. propose a top-k loss is proposed which considers the cases of both class-unbalance and loss-unbalance by focusing more over the hard-to-classify pixels for segmentation of hard exudates in color fundus images. Moreover, a fast version of the top-k loss, named bin loss, is implemented for efficiency, which reduces the time complexity from O (n log n) of top-k loss to O(n), where n is the number of back- ground pixels.

In “AdaResU-Net: Multiobjective Adaptive Convolutional Neural Network for Medical Image Segmentation”, Maria G Baldeon-Calisto et al. present a multiobjective adaptive convolutional neural network (AdaResU-Net) for medical image segmentation that is able to automatically adapt to new datasets while minimizing the size of the network. The proposed AdaResU-Net is comprised of a fixed architecture that combines the structure of the state-of-the-art U-Net with a residual learning framework for more efficient training. Then, a multiobjective evolutionary algorithm (MEA) is proposed to evolve the AdaResU-Net networks with different hyperparameters to optimize both segmentation accuracy and model size.

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