COMPARISON OF OBJECTIVE FUNCTIONS IN CNN-BASED PROSTATE MAGNETIC RESONANCE IMAGE SEGMENTATION

Korea University · MCL Media Communications Lab

Juhyeok Mun[1], Won-Dong Jang[1], Deuk Jae Sung[2], and Chang-Su Kim[1]

School of Electrical Engineering, Korea University, Seoul, Korea[1]

Department of Radiology, Anam Hospital, College of Medicine, Korea University, Seoul, Korea[2]

Introduction

- In CNNs training, the impacts of objective functions on the performance of deep-learning-based algorithms is as enormous as the network architecture
- 3D MR image has severe inter-intra variations that hinder the network from learning dataset
- 3D Fully convolutional network architecture which adapts the feature forwarding method is reliably trained with various objective functions
- Cosine similarity function is the best for training the 3D MR prostate image while various objective functions achieve remarkable performance

Related Work

1) 3D MR Prostate Image Segmentation

- Malmberg et al. propagate initial user annotations from seed voxels to others [1]
- Tian et al. over-segment each image slice into super-pixels, and then dichotomize the super-pixels in to either prostate or non-prostate class based on the graph-cut optimization [2]
- Vincent et al. construct a generative prostate model using appearance, position, and texture features [3]

2) Deep Convolutional Neural Network

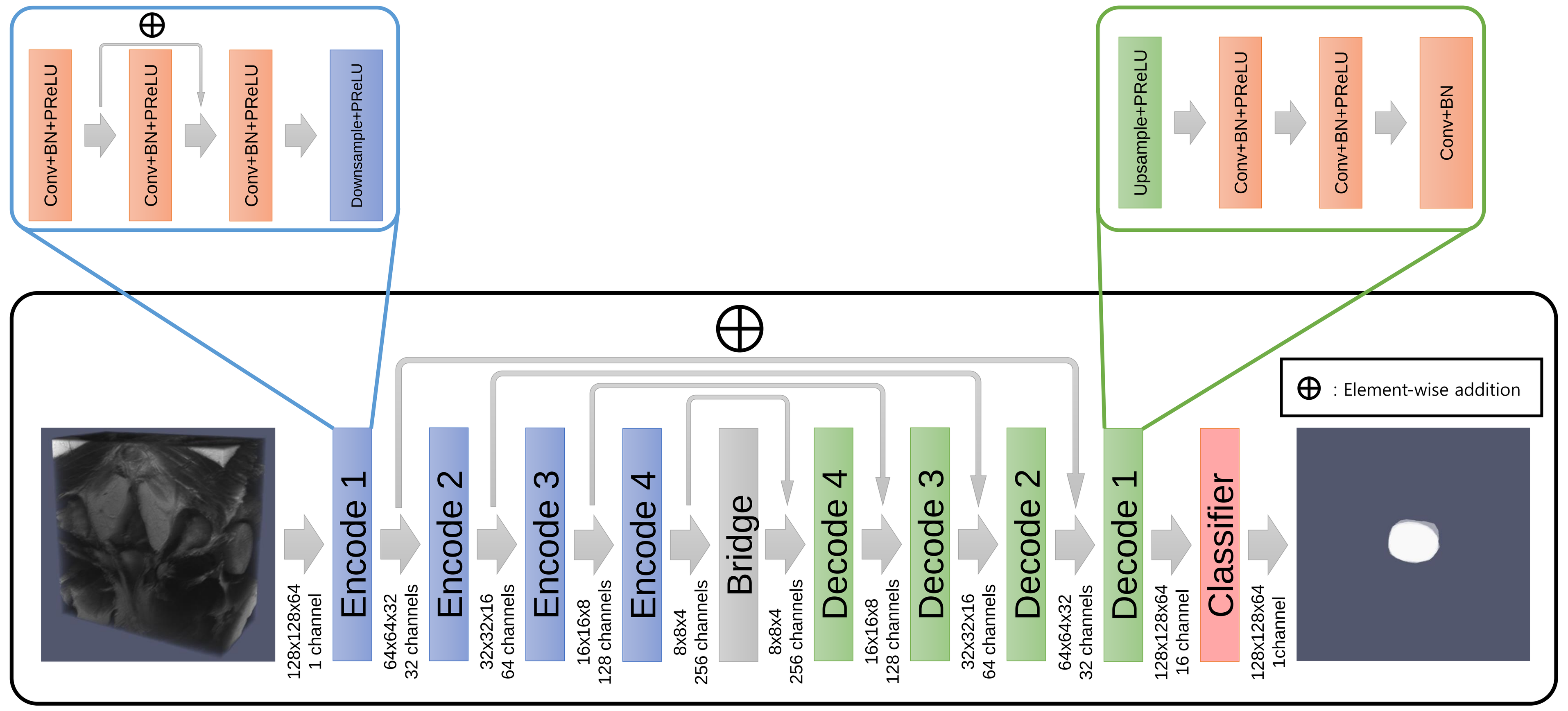
- Dai et al. proposed the fully convolutional network (FCN) for the image segmentation algorithms [4]
- He. Et al. provided the reliable training method that forwards the intermediate features [5]
- Ronneberger et al. adapted the encode-decode architecture and improved the performance with feature forwarding method [6]

3) CNN-based Image Segmentation

- Milletari et al. ameliorated the Ronneberger's algorithm with 3D convolutional layers and objective function which optimizes dice similarity [7]
- Yu et al. adopted the residual feature forwarding and perform the sliding window sampling to obtain segments statistically [8]

Proposed Algorithm

■ Base Network and objective functions



The architecture of the proposed BCNN, which uses the encoding, bridge, decoding, and classification modules.

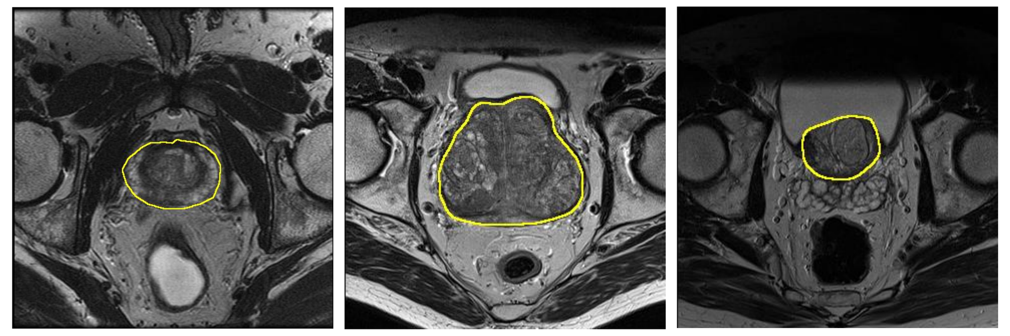
- We construct the baseline convolutional neural network (BCNN) with encode-decode architecture including feature forwarding technique
- The network consists of 3D convolutional, pooling, and deconvolutional layers that process the 3D input data at once
- BCNN learns the given dataset with various objective functions as follow

Table 1. Objective functions used in training:
p_i, q_i are estimated results and ground-truth respectively

Objective function	OTUs	Definition	Gradients
Hamming Distance	$b+c$	$\sum_{i=1}^{N}(p_i^2+q_i^2-2p_iq_i)$	$2(p_j-q_j)$
Euclidean Distance	$\sqrt{b+c}$	$\sqrt{\sum_{i=1}^{N}(p_i^2+q_i^2-2p_iq_i)}$	$\frac{p_j-q_j}{\sqrt{\sum_i(p_i^2+q_i^2-2p_iq_i)}}$
Jaccard Index	$\frac{a}{a+b+c}$	$\frac{\sum_{i=1}^{N}p_iq_i}{\sum_{i=1}^{N}(p_i^2+q_i^2-p_iq_i)}$	$\frac{q_j\sum_i(p_i^2+q_i^2-p_iq_i)-(2p_j-q_j)\sum_i p_iq_i}{(\sum_i(p_i^2+q_i^2-p_iq_i))^2}$
Dice Coefficient	$\frac{2a}{2a+b+c}$	$\frac{2\sum_{i=1}^{N}p_iq_i}{\sum_{i=1}^{N}(p_i^2+q_i^2)}$	$\frac{2q_j\sum_i(p_i^2+q_i^2)-4p_j\sum_i p_iq_i}{(\sum_i(p_i^2+q_i^2))^2}$
Cosine similarity	$\frac{a}{\sqrt{(a+b)(a+c)}}$	$\frac{\sum_{i=1}^{N}p_iq_i}{\sqrt{\sum_{i=1}^{N}p_i^2\sum_{i=1}^{N}q_i^2}}$	$\frac{q_j\sum_i p_i^2\sum_i q_i^2-p_j\sum_i p_iq_i\sum_i q_i^2}{(\sum_{i=1}^{N}p_i^2\sum_{i=1}^{N}q_i^2)^{\frac{3}{2}}}$

Experimental Results

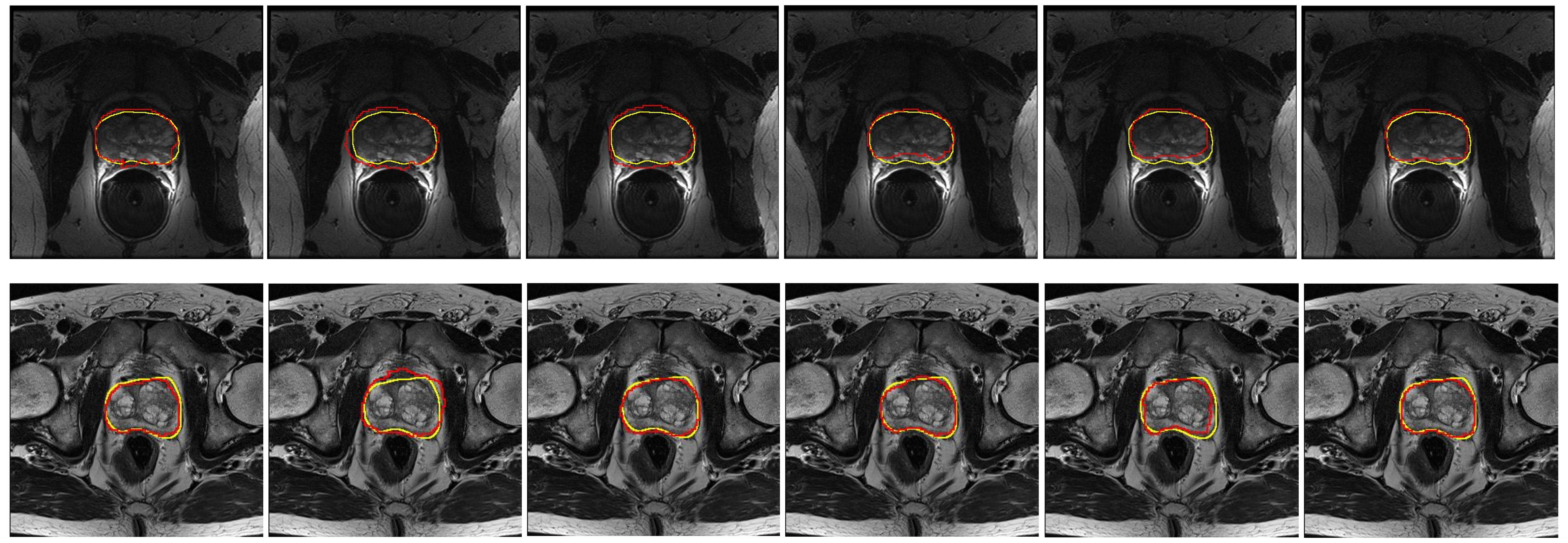
■ 3D MR Prostate Image Dataset



PROMISE12

- Total 50 MR prostate images are given with GT
- The outlines of the prostate are depicted in yellow
- We evaluate algorithms with 10-fold cross validation
- Available: https://promise12.grand-challenge.org

■ Qualitative and Quantitative Results



(a) Cross entropy (b) Jaccard index (c) Hamming distance (d) Euclidean distance (e) Dice coefficient (f) Cosine similarity

Qualitative comparison of the six objective functions for training the proposed BCNN.
The yellow and red boundaries outline the ground-truth and predicted prostate segments, respectively

Table 2. Quantitative results:
The score is Dice coefficient between results and ground-truth

Algorithm	Objective function	Score
BCNN	Hamming distance	0.8366
	Euclidean distance	0.8467
	Jaccard similarity	0.8291
	Dice coefficient	0.8507
	Cosine similarity	**0.8537**
	Cross entropy	0.8275
[8]	Cross entropy	0.8693

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