Semantic Segmentation of Breast Cancer in MRI Using Neural Network Convolution Deep Learning

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1. Abstract

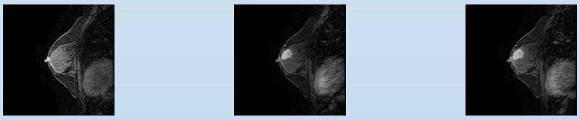
In this research, we plan to develop a semantic segmentation method [1] for breast cancer in MRI by incorporating multiple kernels of different sizes into our original neural network convolution [2] (NNC) deep leaning, which we call multi-size-kernel NNC. We will train our new NNC with MRI images and "gold-standard" manually-segmented breast cancer. We obtained a preliminary result for semantic segmentation by our original NNC with a few cases in a cross validation manner, which showed the feasibility of our deep-learning model.

2. Introduction

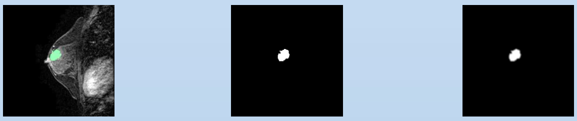
- Breast cancer is the second most common cause of death from cancer in women in the United States, after lung cancer [3].
- Radiogenomics is a new and rapidly evolving field of research aimed at investigating the relationship between imaging biomarkers (radiomics) and genomic data (genomics) [4]. Segmentation of breast cancer in MRI is an indispensable step in radiogenomics, as imaging biomarkers are extracted from segmented breast cancer.
- Deep-learning model [5] called neural network convolution (NNC) was proposed by Suzuki et al. by extending a neural edge enhancer [6] and a massive-training artificial NN (MTANN) [7]. We plan to develop a new version of NNC by incorporating a scheme of multiple kernels of different sizes, which we call multi-size-kernel NNC, for semantic segmentation of breast cancer in MRI.

3. Materials

In this study, we will use a database consisting of 120 breast dynamic contrast-enhanced MRI datasets in 120 patients acquired at the Osaka University Hospital. Figure 1 illustrates an MRI dataset we will use. Each case has MR images with a matrix size of 256x256 pixels in three phases in dynamic contrast-enhanced MRI (a)-(c) and corresponding "gold-standard" manual segmentation (in light green) of breast cancer (d). Figure 1 (e) is a binary version of the manual segmentation. Because the border of manual segmentation may contain an uncertainty, we applied a Gaussian smoothing filter to the binary image to obtain a probability map of being cancer, shown in Fig. 1(f). We will use the probability map as the teaching image and pre-contrast MR image (a) and early-phase MR image (b) as the input for training our NNC model.



(a) Pre-contrast MR image | (b) Early-phase MR image | (c) Delayed-phase MR image



(d) "Gold-standard" manual segmentation by a radiologist | (e) Binary version of the manual segmentation | (f) Teaching image representing a probability map of being cancer

Figure 1: Our database of dynamic contrast-enhanced breast MRI

4. Method to be developed

NNC is a supervised image-based machine-learning technique consisting of a neural network regression model. Unlike other typical deep learning, NNC can learn and output desired images, as opposed to class labels. In this study, we propose a new NNC by incorporating a scheme of multiple kernels of different sizes to enhance objects or object parts of multiple sizes. As shown in Fig. 2, multi-size-kernel NNC consists of kernels of 3 different sizes. The output of our multi-size-kernel NNC is a combination of the outputs of NNCs of different kernel sizes, each of which is expert for specific-sized object (or a specific scale).

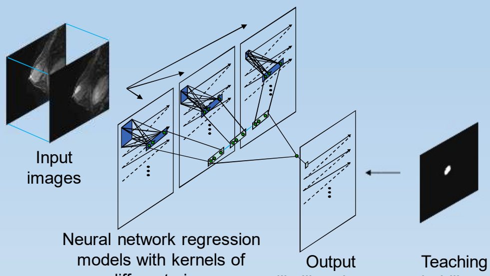
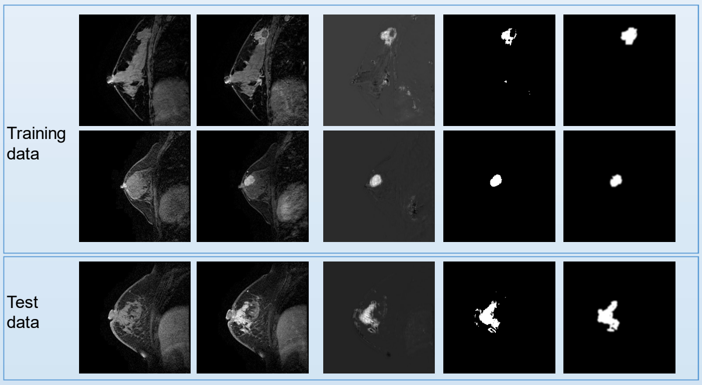


Figure. 2: Schematic diagram of multi-size-kernel NNC

5. Preliminary results based on original NNC

We trained the original NNC with two cases, as shown in Fig. 3, and tested it with the remaining case in the third row in Fig. 3, which is a part of a cross-validation test. The output images and the corresponding images after thresholding are shown in Figs. 3(b) and (c), respectively. "Gold-standard" manual segmentation images are shown in Fig. 3 (d). The result of our NNC trained with only two cases for an unseen case is very close to the "gold standard", showing the robustness of our NNC.



(a) Input pre-contrast and early-phase MR images | (b) Output likelihood maps of our NNC | (c) Output images after thresholding | (d) "Gold-standard" manual segmentation

Figure 3: Semantic segmentation results by our original NNC deep learning model

6. Discussions for study plan

Based on our preliminary result, we believe that NNC is competent for semantic segmentation of breast cancer in MRI, and the new version of NNC with multi-size kernels is expected to improve the performance. We will evaluate the segmentation results by using quantitative evaluation with Dice coefficients. We will compare our NNC with other deep-learning methods for semantic segmentation such as a fully convolutional network (FCN) [8] (which is a special case of NNC) or a U-net [9] (is similar to NNC with a multi-scale approach).

7. Prospective conclusions

We performed a preliminary study for developing and testing our original NNC for semantic segmentation of breast cancer in MRI with 3 cases and showed the feasibility of our model. New NNC deep learning with multi-size kernels will be developed in the rest of my master thesis study.

8. References

1. K. Suzuki, I. Horiba, N. Sugie, and M. Nanki, "Extraction of Left Ventricular Contours from Left Ventriculograms by Means of a Neural Edge Detector", *IEEE Transactions on Medical Imaging*, vol. 23, no. 3, pp. 330-339, 2004.
2. K. Suzuki, J. Liu, A. Zarshenas, T. Higaki, W. Fukumoto, and K. Awai, "Neural Network Convolution (NNC) for Converting Ultra-low-dose to 'Virtual' High-dose CT Images," in *Int. Workshop on Machine Learning in Medical Imaging*, Springer, Cham, 2017, pp. 334–343.
3. C. E. DeSantis, J. Ma, A. G. Sauer, L. A. Newman, and A. Jemal, "Breast Cancer Statistics, 2017, Racial Disparity in Mortality by State," *CA: A Cancer Journal for Clinicians*, vol. 67, no. 6, pp. 439-448, Nov-Dec 2017.
4. H. X. Bai et al., "Imaging Genomics in Cancer Research: Limitations and Promises," *British Journal of Radiology*, vol. 89, no. 1061, 2016, Art. no. 20151030.
5. Y. Lecun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
6. K. Suzuki, I. Horiba, and N. Sugie, "Neural Edge Enhancer for Supervised Edge Enhancement from Noisy Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1582–1596, 2003.
7. K. Suzuki, S. G. Armato, F. Li, S. Sone, and K. Doi, "Massive Training Artificial Neural Network (MTANN) for Reduction of False Positives in Computerized Detection of Lung Nodules in Low-dose Computed Tomography," *Medical Physics*, vol. 30, no. 7, pp. 1602-1617, Jul 2003.
8. J. Long, E. Shelhamer, and T. Darrell, "Fully Convolutional Networks for Semantic Segmentation," in *Proc. of the IEEE conf. on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 3431–3440.
9. O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional Networks for Biomedical Image Segmentation," in *Int. Conf. on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2015, pp. 234–241.