Towards Multiple Enhancement Styles Generation in Mammography

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Abstract

Mammography is a well-established imaging modality for early detection and diagnosis of breast cancer. The raw detector-obtained mammograms are difficult for radiologists to diagnose due to the similarity between normal tissues and potential lesions in the attenuation level and thus mammogram enhancement (ME) is significantly necessary. However, the enhanced mammograms obtained with different mammography devices can be diverse in visualization due to different enhancement algorithms adopted in these mammography devices. Different styles of enhanced mammograms can provide different information of breast tissue and lesion, which might help radiologists to screen breast cancer better. In this paper, we present a deep learning (DL) framework to achieve multiple enhancement styles generation for mammogram enhancement. The presented DL framework is denoted as DL-ME for simplicity. Specifically, the presented DL-ME is implemented with a multi-scale cascaded residual convolutional neural network (MSC-ResNet), in which the output in the coarser scale is used as a part of inputs in the finer scale to achieve optimal ME performance. In addition, a switch map is input into the DL-ME model to control the enhancement style of the outputs. To reveal the multiple enhancement styles generation ability of DL-ME for mammograms, clinical mammographic data from mammography devices of three different manufacturers are used in the work. The results show that the quality of the mammograms generated by our framework can reach the level of clinical diagnosis and enhanced mammograms with different styles can provide more information, which can help radiologists to efficiently screen breast cancers.

Keywords: mammogram enhancement, deep learning.

1. Methods

1.1. Overview

In this work, we present a novel framework, i.e., DL-ME, for multiple enhancement styles generation of mammogram to achieve the following goals:

- The model is expected to enhance mammograms of large dimension without losing resolution.
- The model is with the ability of multiple enhancement styles generation for mammograms, i.e., radiologists can change the enhancement style of the outputs using a manually adjustable switcher.

The task of mammogram enhancement is to find an operator that transforms the histogram of the raw detector-obtained mammogram to a specific shape such that the visualization of enhanced mammogram satisfies a specific observer. The enhancement style of mammogram should be able to adjust manually. Therefore, the presented framework of mammogram enhancement can be expressed as follows:

$$I_{hc} = f(I_{lc}, M; \Theta). \tag{1}$$

Here, I_{lc} is the low-contrast (lc) raw detector-obtained mammogram and I_{hc} is the high-contrast (hc) enhanced counterpart. $f(\cdot)$ denotes the operator of a specific enhancement style. Θ is the parameters of enhancement operator. Moreover, M is a switch map to control the enhancement style of the output. In this work, we present the DL-ME model to approximate the enhancement operator for mammograms. The DL-ME model is implemented as a multi-scale cascaded residual convolutional neural network (MSC-ResNet), which performs the mammogram enhancement from coarse scale to finer one. The output in the coarser scale is used as part of inputs for the finer scale to improve the enhancement performance. To realize different enhancement style generation of mammogram, a switch map M is also served as part of inputs in all the scales to control the enhancement style of the outputs. The overall architecture of the DL-ME model is shown in Fig. 1.

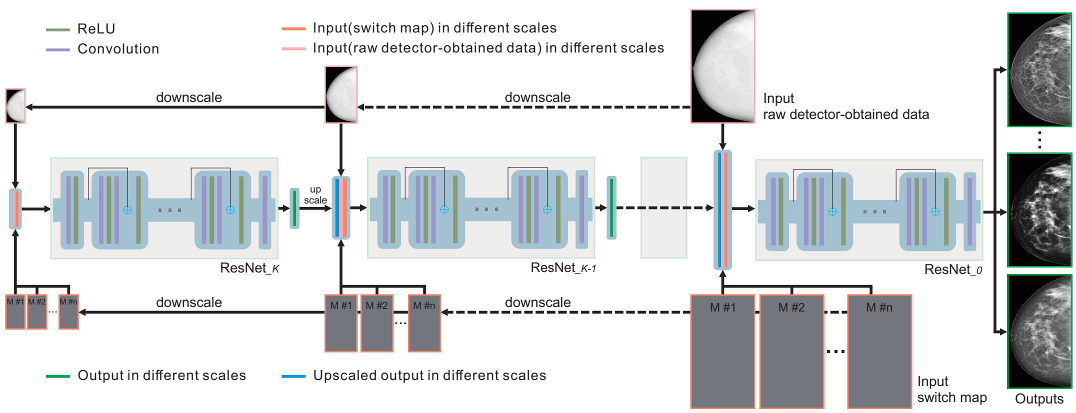

Figure 1: The architecture of the DL-ME model.

1.2. Network Architecture

Intuitively, many of network architectures (Ronneberger et al., 2015; Vincent et al., 2010) can be used to implement mammogram enhancement in a single scale. Because of promising performance of the ResNet (He et al., 2016), in this work, we adopt a simplified ResNet. For simplicity, the single-scale ResNet for mammogram enhancement is denoted as SS-ResNet in the following. Specifically, the SS-ResNet is consisted of a series of 3×3 convolutional layers. The first layer is composed of one convolution and one Rectified Linear Units (ReLU) (Krizhevsky et al., 2012). The middle layers are a sequential of residual blocks and the last layer is just one convolution. In our SS-ResNet, the batch normalization (BN) (Ioffe and Szegedy, 2015) is not adopted for simplicity, because no significant improvement was achieved with BN, according to our experiments. In addition, no zero-padding is employed during the convolution operations in the network, therefore the inputs should be padded enough to avoid dimension mismatching in the output.

To achieve the enhancement of large dimension mammograms, a multi-scale cascaded strategy, i.e., MSC-ResNet, is adopted. ResNet$_k$ in the MSC-ResNet is an enhancement operator for mammogram in the kth scale level. The enhanced mammogram in the coarser scale is considered as a kind of priori information to improve the enhancement performance in the successive finer scale, which finally would yield promising enhanced mammogram in the original scale.

2. Results

The experimental results are shown in Fig. 2. In the result, Hologic, Anke, and Gitto are three mammography device manufacturers. The Raw(Hologic) and Reference(Hologic) denote respectively the raw detector-obtained and the enhanced mammograms obtained from the Hologic device; SS-ResNet(Hologic) is the results of ResNet without multi-scale cascaded strategy; DL-ME(Hologic), DL-ME(Giotto), and DL-ME(Anke) denote three enhancement styles generated by the presented DL-ME model. The SS-ResNet model can improve the contrast to some extent. However, the resolution is decreased. On the contrary, the cascade strategy adopted by the DL-ME model can significant improve the mammogram enhancement performance. More importantly, the DL-ME model can effectively learn the enhancement styles of different mammography devices, as could be found in Fig. 2(d)-(f). In addition, we selected 10 cases of mammograms, which are difficult to be distinguished as benign or malignant, for two experts to diagnose. One of the experts' results is 70% (DL-ME$_{Anke}$), 70% (DL-ME$_{Hologic}$), 80% (DL-ME$_{Gitto}$), and 80% (Reference$_{Hologic}$), respectively. Experts integrated the three styles of images and the final accuracy is 80%, which is higher than that of the mammograms generated by the Hologic device, i.e., 70%. The diagnose results of the two experts indicate that multiple enhancement styles generated by the DL-ME model could help radiologists to efficiently screen breast cancers.

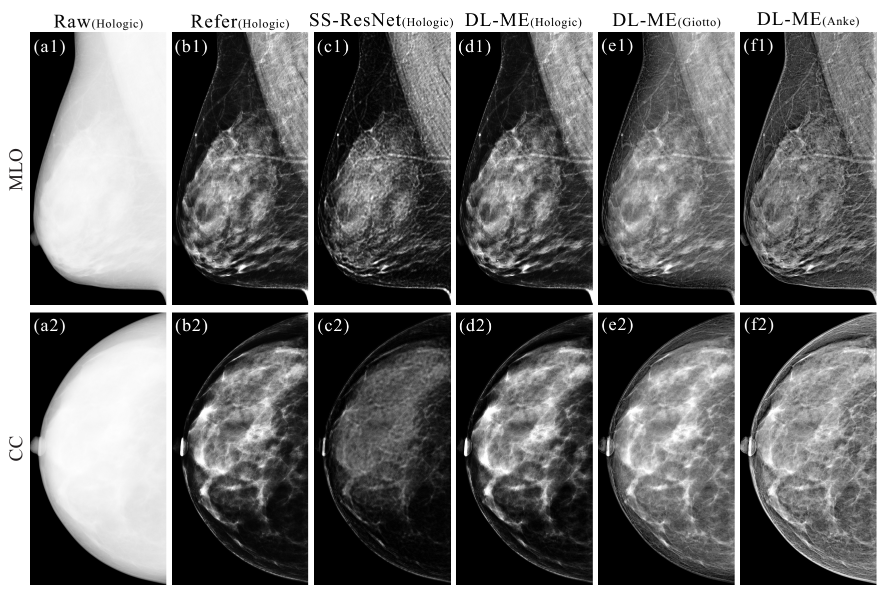

Figure 2: Enhancement of the raw detector-obtained mammograms from the mammography device of Hologic. From (a) to (f): Raw(Hologic), Reference(Hologic), SS-ResNet(Hologic), DL-ME(Hologic), DL-ME(Giotto), and DL-ME(Anke). The upper row shows a case of MLO view and the lower row shows a case of CC view.

References

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *Computer Science*, 2015.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of machine learning research*, 11(Dec):3371–3408, 2010.