Deep Vectorization Convolutional Neural Networks for Denoising in Mammogram Using Enhanced Image

Varakorn Kidsumran[1]~~[0000-1111-2222-3333]~~ and Yalin Zheng[2]~~[1111-2222-3333-4444]~~

[1] Rajamangala University of Technology Isan, Surin Campus, 32000, Thailand
[2] University of Liverpool, Liverpool, L69 3GA, United Kingdom
varakorn.ki@rmuti.ac.th,yalin.zheng@liverpool.ac.uk

Abstract. Mammography is an X-ray image of the breast which ~~the radiologists use to diagnose breast cancer in the early detection stage~~. However, in many cases, it is not easy to identify a sign of cancer as tumour or malignancy due to clouding various noise patterns caused by the low dose radiation from the X-ray machine. ~~Then, mammogram~~ denoising is an important process to improve the visual quality of mammogram to help the radiologist's diagnosis when they screening mammogram. This paper introduces denoising deep vectorization convolutional neural networks using an enhanced image from direct contrast in a wavelet domain for training. Then, Denoised mammogram is obtained from mapping between the original and enhanced image. The experimental results revealed that the proposed method can effectively suppress various noises in mammogram by comparison to traditional denoising methods.

Keywords: Mammography, Deep Vectorization Convolutional Neural Networks, Enhanced image, Wavelet Domain.

1 Introduction

Breast cancer is the most common cancer in the world. It was estimated that there were more than 522,000 deaths from breast cancer in 2012 [1] because the patient was diagnosed in the very late stages. At present, mammography screening is the most effective tool in the early detection stage. However, the misdiagnosis rate is approximately 20% [2] because mammograms from a low dose X-ray machine are corrupted by noise that makes their interpretation very difficult. Thus, ways to achieve robust reductions of noise in mammography has become a very important issue to improve the rate of correct diagnosis and decrease the breast cancer mortality rate.

Digital image processing has been widely used to improve the visual quality of images, and over the past decades, several denoising methods have been developed to reduce noise in mammograms. To adapt discrete scales to fit the size of the abnormal area, such as the size of micro-calcifications, Heinlein *et al.* [3] introduced an integrated wavelet based on filter banks derived from continuous wavelet transformation, which has more flexibility to detect breast cancer. Mencattini *et al.* [4] developed a discrete dyadic wavelet transform to reduce variable noise estimated by a local iterative fuzzy method using adaptive thresholding. Elsherif *et al.* [5] introduced a wavelet packet to remove noise and enhance contrast in mammograms, but the effectiveness of this method depends on enhancement parameters. Matsuyama *et al.* [6] modified wavelet coefficients to remove noise in mammograms using hierarchical correlation based on an undicimated wavelet transform. This method is very simple, fast, and provides better visual quality compared to conventional unidicimated wavelet transforms [7].

Some work has investigated noise suppression in natural images. Buades *et al.* [8] proposed a nonlocal means algorithm to preserve the structure in a digital image based on analysis of the noise model that is defined by the difference between a digital image and its denoised version. In this method, the visual quality of the image depends on filtering parameters. Dabov *et al.* [9] proposed principal component analysis (PCA) as part of a 3D transform that applied a shape adaptive transform to the input image. Their experimental results showed that this denoising method can preserve the detail of the image, but introduces some artifacts. Ender [10] developed block-matching and 3D filtering (BM3D) for Magnetic Resonance Imaging (MRI). The performance of this method is superior to BM3D model. Shuhang *et al.* [11] proposed weighted nuclear norm minimization (WNNM) for image denoising by exploiting the image nonlocal self-similarity. The experimental results superior than state of the art denoising method both quantitative measure and visual perception quality. Luisier *et al.* [12] introduced a new Stein's unbiased risk estimator (SURE) by minimizing an estimate of the mean square error between a noisy and clean image. This approach illustrated better denoising performance in peak signal-to-noise ratio (PSNR) compared to the BayerShrink [13] and Bayesian least squares-Gaussian scale mixture (BLS-GSM) [14] methods. Blu *et al.* [15] modified the SURE method by adding a linear combination of the primary denoising process referred to as a linear expansion of thresholds (LET). The results suggested that the SURE-LET scheme led to improved images. Matsuyama *et al.* [16] proposed a SURE-LET image denoising method with directional lapped orthogonal transforms (DirLOTS), which differs from the SURE-LET method, and was used in [9] by adapting hierarchical tree construction of directional lapped orthogonal transforms as a shrinkage function in a wavelet transform to overcome the geometric problem in the SURE-LET method.

In addition, many researchers have investigated improvements to median filtering in denoising files. Jianxiong *et al.* [17] presented the local statistical characteristics based on median filtering to remove noise. This method can be used to preserve edges in an image. Vikrant *et al.* [18] proposed a non- iterative adaptive median filter in which the experimental results were successful in suppressing impulses of high intensity noise. Shulei *et al.* [19] improved the median filter by adding a filter function, which demonstrated good detail after filtering. Xiaofeng *et al.* [20] modified the median filter further by designing comfortable direction templates to remove noise in ultrasound images. The advantage of this method is that it preserves edges and provides significant detail.

Recently, deep learning networks have become a role model to reduce noise in images. Burger *et al.* [21,22] proposed multi layer perception (MLPs) for image denoising. The efficiency of MLPs depends on its architecture and the number of training examples. Jain and Seung [23] denoised a natural image successfully using convolutional neural networks (CNNs). This method demonstrated higher performance compared to the wavelet and Markov random field (MRF) methods. Xie *et al.* [24] introduced stacked sparse autoencoders that combine sparse coding and deep networks pre-trained with a denoising auto-encoder (DA). This method delivered performance comparable to the

K-SVD algorithm. Agostinelli *et al.* [25] demonstrated a state of the art denoising method that uses adaptive multi column deep learning networks. This can reduce a variety of different noise types. Gondara [26] developed convolutional denoising autoencoders (CDA) for medical images. The denoising performance of this method produced high quality in objective tests such as structural similarity index (SSIM) but in subjective tests, the denoising quality decreased when the noise level increased. Ren *et al.* [27] proposed vectorization convolutional neural network (VCNN) to improve visuallity of the image. The experimental results save time computing and can be applied to a different platform.

However, in the real world, noise in mammogram come from various sources such as quality of X-ray machine, the experience of user, even physical of breast. Then, exist denoising deep neural networks using noise model not suitable for ground truth mammogram. To overcome the limitations of prior work, denoising deep vectorization convolutional neural networks using enhanced image is proposed to robust noise in mammogram. Denoising neural networks can be estimate various noise from enhanced image. Noise free image is obtained by mapping enhanced image and original image. This scheme can decrease specific noise types in mammogram effectively.

Rest of this paper is organized as follows: section II introduces detail of mammogram Section III decribes the proposed method. Section IV presents the experimental results of the denoising method compared to state of the art methods, such as, BM3D-MRI, WNNM and VCNN, followed by conclusion in section V.

~~2 Background~~

~~Mammogram is a picture of breast that clouding with various noises as shown in Figure 1. The dark areas are normal fatty breast tissue and the lighter areas are denser tissue. The whiter spots are calcifications which can be divided in 2 types such as marcocalcification and microcalcification. Where, the cluster of microcalcification can be a sign of cancer.~~

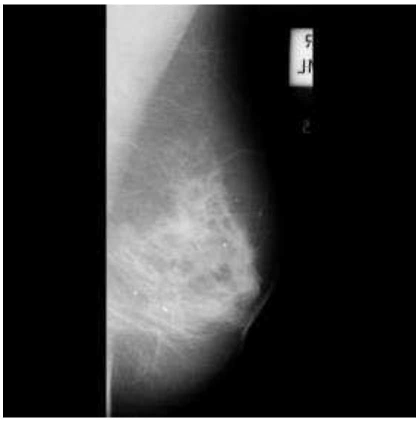

Fig. 1. Original mammogram

3 The proposed method

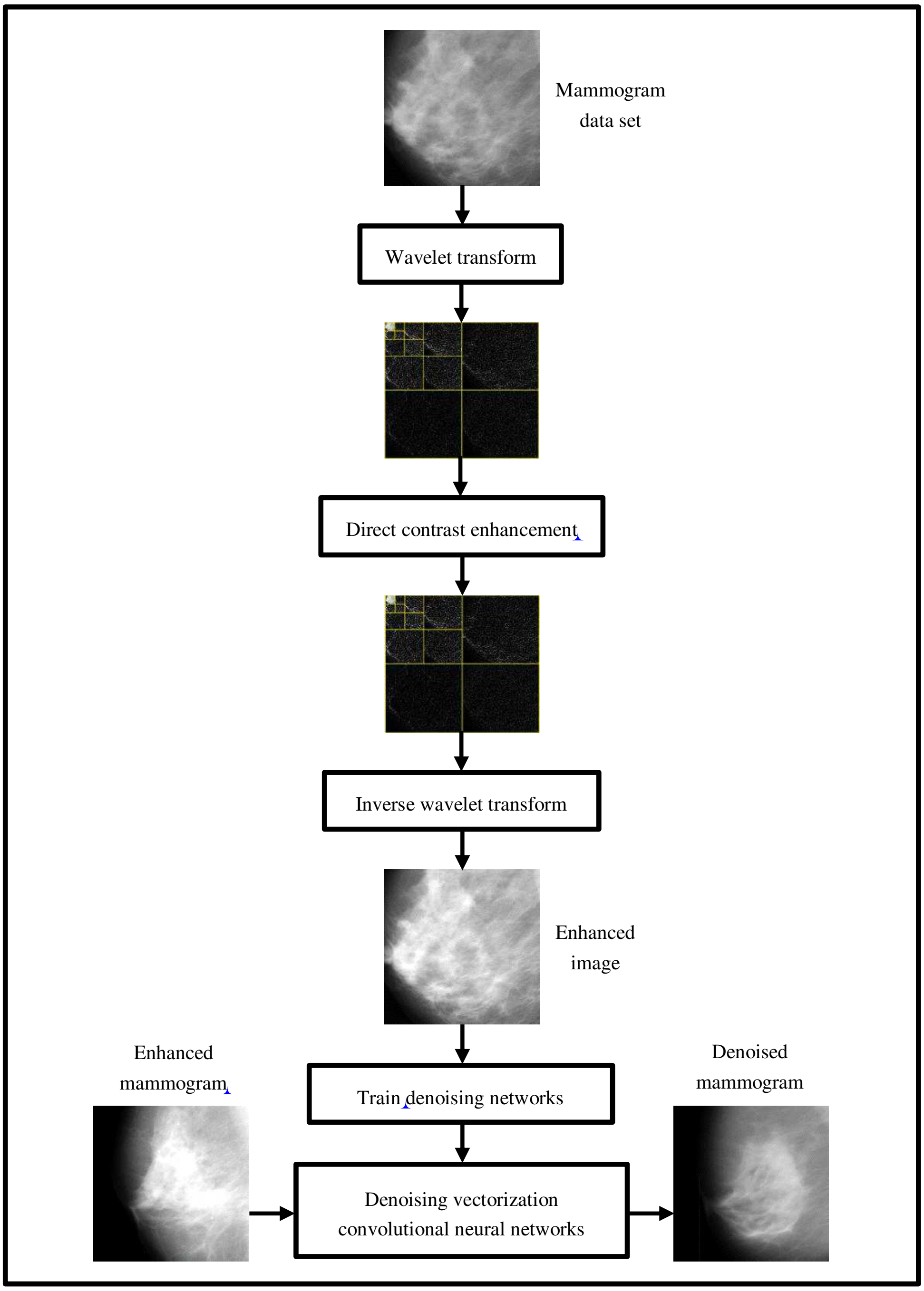

Fig. 2. The proposed method workflow

Figure 2 illustrates the flowchart of proposed method for suppress noise in mammogram which consits of 5 steps are described as follows.

- ~~In this step,~~ the original mammogram is cropped to 512×512 pixels and decomposed with 4-level Daubechies-4 discrete wavelet transform.
- Direct contrast technique is used to enhance contrast in original mammogram by multiplying the constant value (k) to all detail subbands in wavelet domain.

$$D^{n}_{l,global}(x,y) = k \cdot D^{n}_{l,original}(x,y) \quad (1)$$

- The enhanced image is obtained from inverse wavelet transform. Then, all detail features in mammogram are boosted including noise.
- The enhanced image is used to train in a training data set that suitable for apply to real noisy mammogram.
- After training, denoised mammogram is obtained from mapping enhanced image to original mammogram image.

$$f = argmin_{f} \sum_{i=1}^{N} L\|f(y_i) - x_i)\|_2^2 \quad (2)$$

Where, f is the vectorization convolutional neutral network and L as the mean squre error. Enhanced image that courrupted with various noise (y) as input and origianl image (x) as output. Then, the denoised image depends on minimization of the mean square error function between the desire image and the target image.

4 Experimental results

4.1 Data

Mammogram images used in this experiment are provided by the mini-MIAS database of mammograms that contains 322 images [28]. ~~Where,~~ 161 images are randomly selected for training data and 161 images for test data, repectively. Both training and test data sets are cropped from 1024 × 1024 to 512 × 512 pixels size**.**

4.2 Experimental results

State of the art denoising method such as BM3D-MRI, WNNM and VCNN are selected to comparison with the proposed method which code programs are online available. To evaluate the performance of the proposed method, peak signal-to-noise ratio (PSNR) was used to measure the quality of the resulting image compared to well-known denoising algorithms.

Figure 3 shows an example denosing result obtained from various denosing methods compared to the original. It can be seen that BM3D-MRI, WNNM and VCNN can not preserve edges and significant detail as shown in the red square on the bottom left. In comparison, the denoising result obtained from the proposed method showed more higher visual quality among other methods.

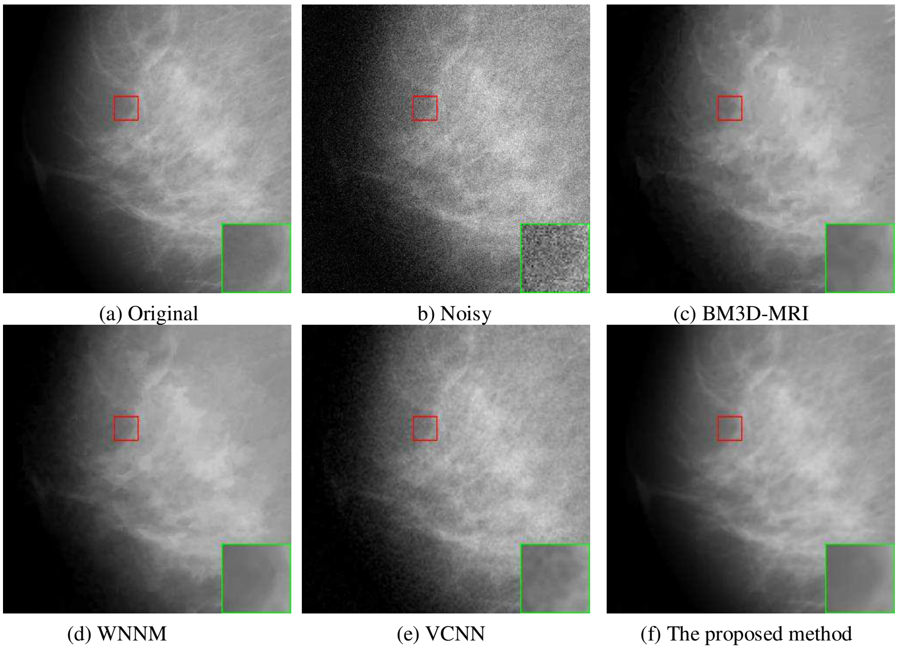

Fig. 3. Denoising results (a) Original, b) Noisy, (c) BM3D-MRI, (d) WNNM, (e) VCNN (f) The proposed method

Table 1. Comparison of average PSNR results in different denoising methods.

	NOISY	BM3D-MRI	WNNM	VCNN	THE PROPOSED METHOD
PSNR	20.17	23.01	33.17	34.11	**42.39**

Table I demonstrates that the performance of denoising by comparing with PSNR of BM3D-MRI, WNNM, VCNN and the proposed method. The average PSNR of the proposed method is higher than the other methods. This clearifies that various noises in mammogram are effectively suppressed.

5 Conclusion

Image denoising has been important to improve visual quality of an image. Epecially, medical image such as mammogram that widely used to diagnose breast cancer in the early detection stage.

In this study, a denoising deep vectorization convolutional neural networks using enhanced image replace synthetic noisy image. This strategy breakdown the limitation existing denoising deep neural networks that suitable for noise model has been train in training data set.

The experimental results illustrated that the proposed method can be remove complex noise patterns and improved significant detailed features in mammograms, such as micro-calcification and malignant tissue. The advantages of this method can help radiologists diagnose breast cancer more accurately during screening mammograms.

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