Effect of Image Variation on Computer Aided Detection Systems

S.P.Rabbani[1], P.Maduskar, R.H.H.M. Philipsen, L.Hogeweg and B. van Ginneken[2]
School of Technology and Health, KTH Royal Institute of Technology, Stockholm, Sweden [1]
Diagnostic Image Analysis Group, Radboud University Medical Center Nijmegen, The Netherlands [2]

ABSTRACT

As the importance of Computer Aided Detection (CAD) systems application is rising in medical imaging field due to the advantages they generate; it is essential to know their weaknesses and try to find a proper solution for them. A common possible practical problem that affects CAD systems performance is: dissimilar training and testing datasets declines the efficiency of CAD systems. In this paper normalizing images is proposed, three different normalization methods are applied on chest radiographs namely (1) Simple normalization (2) Local Normalization (3) Multi Band Local Normalization. The supervised lung segmentation CAD system performance is evaluated on normalized chest radiographs with these three different normalization methods in terms of Jaccard index. As a conclusion the normalization enhances the performance of CAD system and among these three normalization methods Local Normalization and Multi band Local normalization improve performance of CAD system more significantly than the simple normalization.

Key words: Image Normalization, Local normalization, Multi band local normalization, Chest Radiography, Lung segmentation, Computer Aided Detection

1. PURPOSE

Computer Aided Detection (CAD) systems are gaining popularity for clinical applications to assist in accurate and fast diagnosis. However, CAD systems are likely to suffer from a common practical problem, CAD system performance declines when the train and test data set are not from the same source. The reason behind this behavior could be explained by the different initial data collecting conditions. One possible solution is to train the system individually for different datasets but it greatly undermines the practicality of the CAD system and it affects its overall performance.

To make CAD system less sensitive to image variations and to tackle the aforementioned problem, several approaches could be considered as a possible solution: (1) implementation of the invariant features, (2) deriving a more robust algorithm for the CAD system and (3) employing image normalization prior to implementing the CAD system on the purposed data as preprocessing step. In this paper the third approach is employed and performance of the lung segmentation CAD system is investigated on normalized chest radiographs of different sources. Three different normalization methods are applied as a possible preprocessing step: (1) Simple Normalization (2) Local Normalization and (3) Multi band Local Normalization.

2. METHOD

2.1 DATA

In this work data consists of CXRs from six sources: source 1. Image by digital Odelca-DR system with slotscan detector (Delft Imaging Systems, The Netherlands); source 2. Images by digital EasyDR system (Delft Imaging

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Systems, The Netherlands) with a Canon CXDI detector; source 3. Digitized analog film CXRs from the JSRT database[8]; Source 4. Images by digital MobileDaRt system (Delft Imaging Systems, The Netherlands) with a Canon CXDI detector; Source 5. Images by a THORAX/MULTIX FD (Siemens, Germany) with a Siemens FD-X detector; source 6. Images by a DigitalDiagnost unit (Philips Medical Systems, The Netherlands) with a Pixium 4600 detector. The CAD system is trained by 100 images from source 1 and is tested on 20 images from each of the six mentioned sources. Please not that all these images are resize to 1024-pixel width.

2.2 SIMPLE NORMALIZATION

Different intensity range of different images is treated by a linear solution. A scaling gain is applied to set the average value to zero and the standard deviation to 1 for all images. The contrast and brightness of images of different sources are adjusted homogeneously as a consequence of this procedure.

2.3 LOCAL NORMALIZATION

In this experiment the images are normalized locally, each pixel is affected exclusively by its surrounding neighborhood. This approach is the same as the preprocessing step in a paper by Schillman et al.[2] This approach is defined as:

$$L_{LN} = \frac{(L - \tilde{L})}{\left(\widetilde{L^2} - (\tilde{L})^2\right)^{1/2}} \qquad (1)$$

The image intensity, Gaussian blurring and locally normalized image are indicated by$L$, $\tilde{L}$ andL_{LN} respectively. In this method the control parameter sigma (σ_{LN}), the scale parameter for Gaussian blurring, determines the neighborhood size according to which each pixel is normalized. It is the key property of this method is that it is possible to implement it with different scales. The above formula can be interpreted as normalizing local intensity deviation from the average over the local standard deviation.

2.4 MULTI BAND LOCAL NORMALIZATION

This approach is also a nonlinear normalization technique in which each image is broken to five frequency band and each sub band is treated individually with local normalization at a certain scale. The hierarchical unsharp masking technique that is implemented to derive these sub bands is the same as the one in a paper by Stahl et al[3], Figure 1 illustrates this procedure.

Having different frequency bands makes it possible to avoid blurring the lower frequencies components of the image by applying a smaller scale local normalization to them while the higher frequency bands are locally normalized with a larger scale. Therefore, sub bands 1 to 5 are locally normalized by the scale of 64, 60, 56, 52 and 48 pixels respectively. Local normalization cause an artifact in homogenous areas, hence a correction constraint is implemented on each sub band individually following the local normalization process. To decrease these artifacts, homogenous areas or areas with low variance in each sub band are blurred. Pixel value in variance image of each sub band is derived by equation (2):

$$variance = \frac{\sum_1^{x_{dimention}} \sum_1^{y_{dimention}} (pixel(x,y) - mean)^2}{Number\ of\ pixels} \qquad (2)$$

The condition that makes a pixel falls in homogenous area is expressed in (3). Pixels holding this condition are then replaced by average value in their corresponding neighborhood of size 3 by 3 pixels.

$$Pixel\ value\ in\ variance\ image\ of\ sub\ band_{(i)} < \frac{variance\ of\ sub\ band\ image_{(i)}}{9} \qquad (3)$$

Prior to the final step, a scaling gain is employed to each sub band aiming to make standard deviation of corresponding sub bands in all images equal to average standard deviation of training dataset. The scaling gain is defined in (4).

$$Gain\ Ratio = \frac{reference\ average\ variance\ value\ for\ sub\ band\ "\ i"}{variance\ value\ of\ the\ sub\ band\ "i"} \qquad (4)$$

Eventually these individually processed sub bands are added up and create normalized image containing all frequency sub bands.

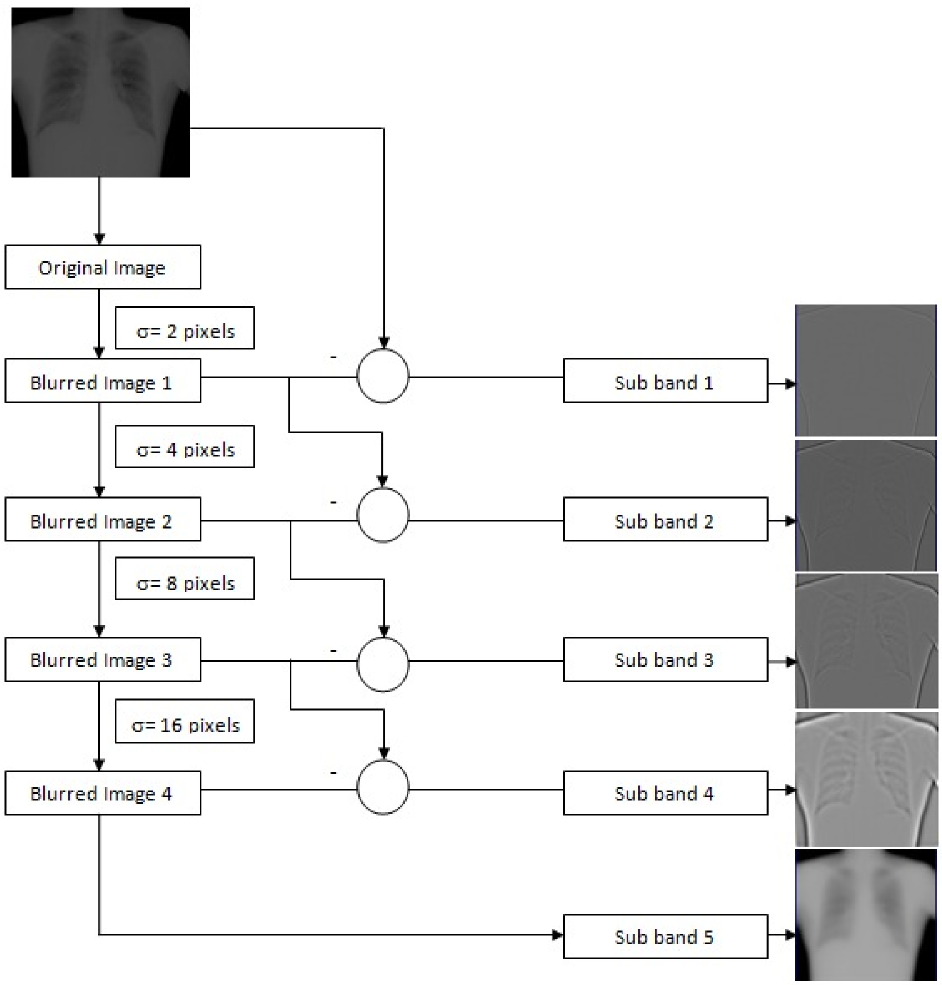


Figure 1 Deriving the sub band images process. Window level for four first sub bands is (100/0) and for the last sub band and the original image is 2500/4000.

To better convey the whole procedure, all of the implemented steps are depicted in Figure 2 and the general fellow chart of this method is illustrated in Figure 3.

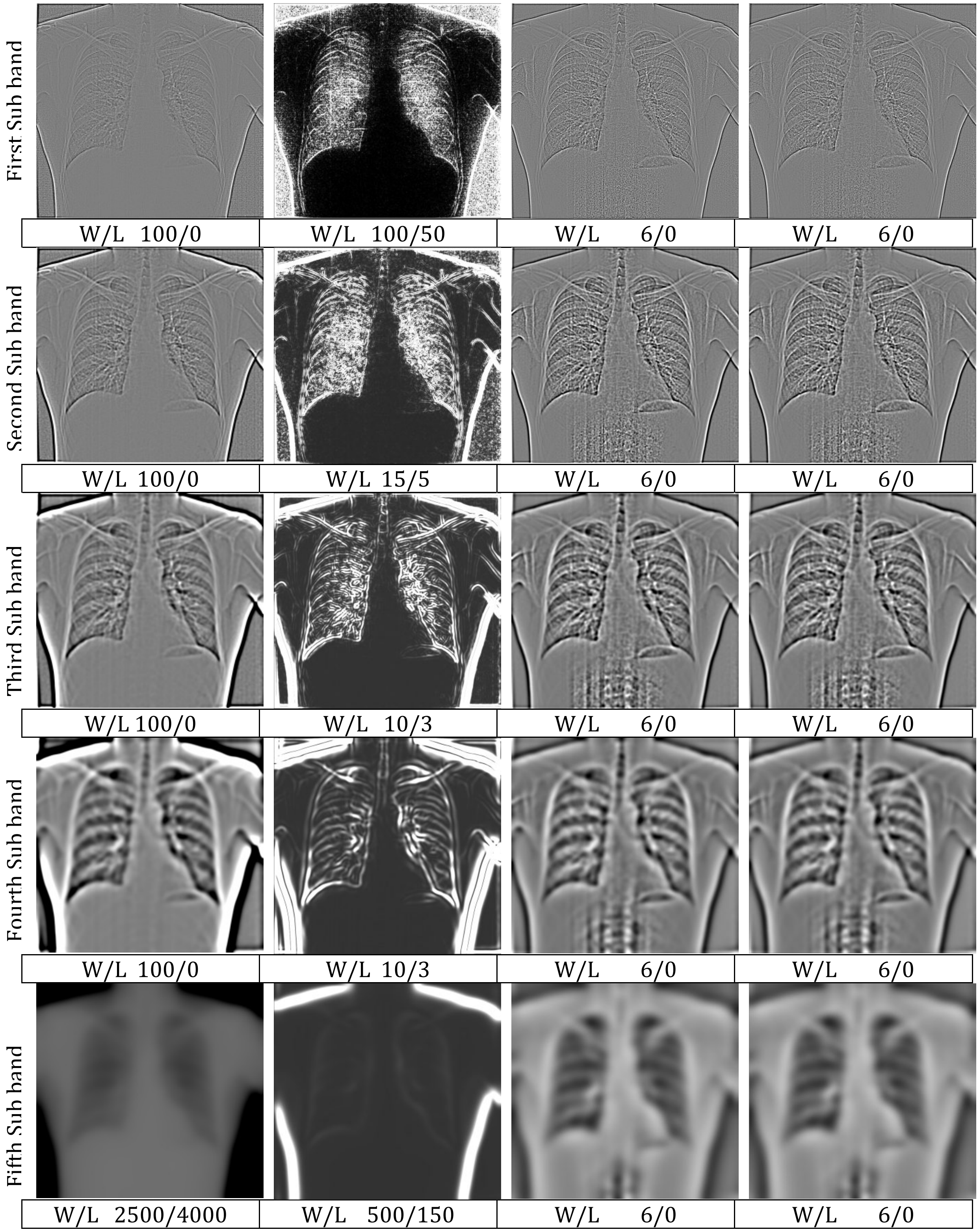


Figure 2. Unprocessed sub band images, variance images, locally normalized images and Corrected locally normalized images from left to right column wise.

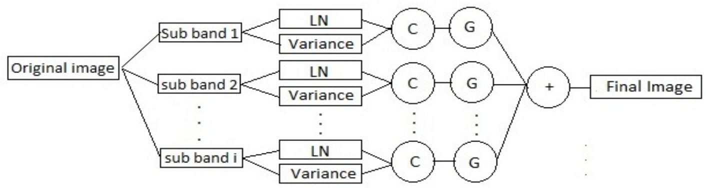


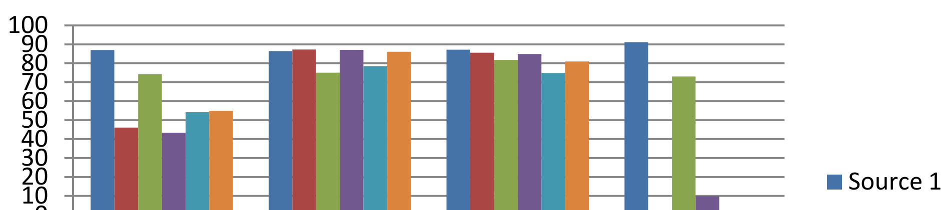
Figure3. Fellow chart of Multi band local normalization process

2.5 LUNG SEGMENTATION

In order to find out how efficient these normalization methods are, lung segmentation is applied on the normalized images. The lung segmentation algorithm that is implemented in this paper is the same as the one in van Ginneken et al.[5] The employed classifier for lung segmentation purpose is kNN pixel classifier; the employed features are Gaussian derivatives of different scales up to second order and the x, y position of each pixel.

3. RESULTS

The overlap ratio of the lung segmentation technique is measured by Jaccard index; the averaged Jaccard index is illustrated by percentage in Figure 1 both for normalized and unprocessed images. It can be easily inferred that for unprocessed images this measure is high only for the data from the same source as training data. On the other hand the overlap ratio for normalized images is almost in the same range for images from all sources. Figure 5-6 illustrates unprocessed and normalized images and their corresponding detected and manually annotated lung masks.



	Simple Normalization	Local Normalization	Multi band Local Normalization	Unprocessed Images
Source 1	87.06	86.46	87.21	91.19
Source 2	46.12	87.29	85.63	0.6
Source 3	74.24	75.1	81.79	73.03
Source 4	43.38	87.1	84.92	9.85
Source 5	54.1	78.44	74.92	0.02
Source 6	54.89	86.14	80.96	0

Figure 4. Comparison between the average overlap ratio of the Simple normalization, local normalization, multi band local normalization and unprocessed images.

4. DISCUSSION AND FUTURE WORKS

In this work the normalization methods are applied only to chest radiographs for lung segmentation purpose, although there is no reason to limit this simple and effective solution only for the above mentioned application. In terms of future work, the correction and gain step in the multi band local normalization could be further developed and as a consequence increase the robustness of this method.

5. CONCLUSION

Linear and non linear normalization methods enhance the performance of the lung segmentation technique up to some level. Comparison between the effect of linear and nonlinear normalization methods specifically on chest radiographs shows that nonlinear methods are more influential. According to output images, the proposed new non linear normalization technique, multi band local normalization, outperforms the other two methods. However, the overlap measures of local normalization and multi band local normalization are comparable.

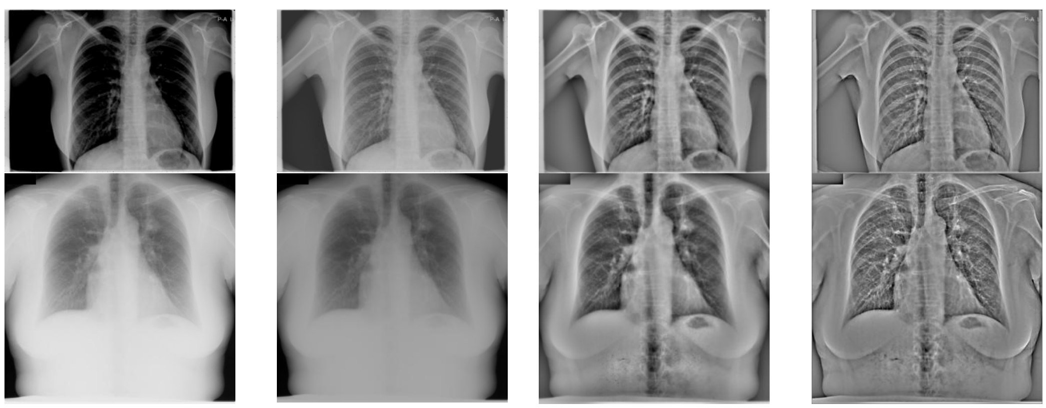


Figure 5. Each row illustrates an image from one of the datasets; Column 1: Unprocessed images, column 2: Simply normalized images, column 3: Locally normalized images, column 4: Multi band locally normalized images.

Figure 6. This figure shows the lung mask of cases in Figure 3, Column 1: Manually annotated lung mask, Column 2: Lung segmentation of unprocessed image, column 3: Lung segmentation of Simply normalized image, column 4: Lung segmentation of locally normalized image, column 5: Lung segmentation of multi band locally normalized image.

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