Title
Decision Support Systems for Radiologists based on Phase Stretch Transform

Author
Suthar, Madhuri

Publication Date
2016

Peer reviewed|Thesis/dissertation

University of California
Los Angeles

Decision Support Systems for Radiologists based on Phase Stretch Transform

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Science in Electrical Engineering

by

Madhuri Suthar

2016

Abstract of the Thesis

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by

Madhuri Suthar

Master of Science in Electrical Engineering

University of California, Los Angeles, 2016

Professor Bahram Jalali, Chair

Phase Stretch Transform (PST) is a physics-inspired computational approach developed in Jalali lab for feature enhancement in images. Here, it is applied to medical images. The results of its application to X-rays leads to development of an assistance tool for diagnosis of pneumothorax in X-ray images. The tool, which is first-of-its-kind, helps in locating the boundary of a collapsed lung, a life-critical clinical examination which is otherwise difficult for a radiologist to locate with a naked eye.

Additionally, PST is applied to other medical images, such as histology and mammograms, to demonstrate feature enhancement. The resulting edge detection map offers promising application in segmentation and analysis of medical images which is explored here. Further, texture segmentation using PST is also demonstrated.

The thesis of Madhuri Suthar is approved.

Fabien Scalzo

William Kaiser

Bahram Jalali, Committee Chair

University of California, Los Angeles

2016

To my parents...

who have stood by me

always

Table of Contents

List of Figures

Acknowledgments

I would like to express my sincere gratitude to Prof. Bahram Jalali for all his support and guidance throughout my studies at UCLA. I would like to thank Prof. William Kaiser and Prof. Fabien Scalzo for being on my thesis committee and offering invaluable suggestions. To my fellow lab mates, particularly Ata Mahjoubfar, Jacky Chan and Yunshan Jiang for all their help in making me complete this project. Last but not the least I would like to thank my family and friends for all their support.

This work was partially supported by the National Institutes of Health (NIH) grant no. 5R21 GM107924-03 and the Office of Naval Research (ONR) Multidisciplinary University Research Initiatives (MURI) program on Optical Computing.

Vita

2010–2014	Bachelor of Technology (B.Tech), Electronics and Communication Engineering, Indian School of Mines, Dhanbad, India.
2014–2015	Research Assistant, Electrical Engineering Department, IIT Bombay, India.
2015–present	Graduate student, Electrical Engineering Department, UCLA, USA.

CHAPTER 1

Introduction

Quantitative research in medical imaging often involves use of image processing tools. This leads to development of decision support systems by the aggregation of image processing techniques with machine learning. Edge detection, being one of the important image processing techniques, locates sharp variations of brightness in an image and is used widely for object detection, recognition and classification. Phase Stretch Transform (PST), a physics inspired digital image transformation emulates propagation of electromagnetic waves through a diffractive medium with a dielectric function that has warped dispersive (frequency dependent) property [1], [2].

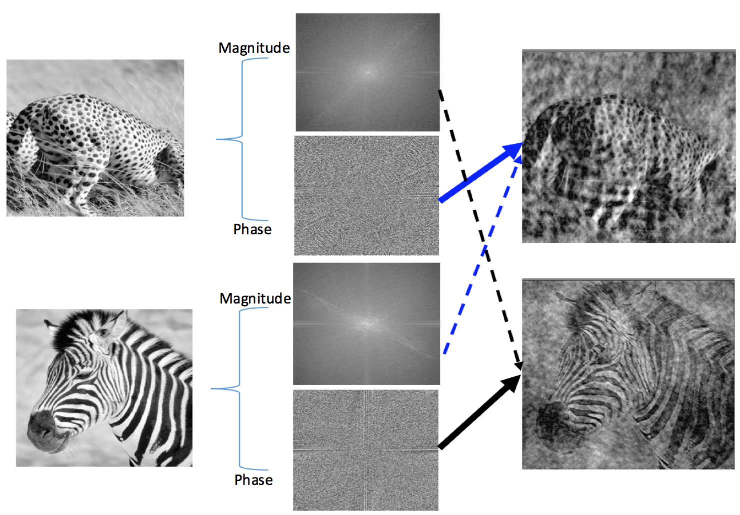


Figure 1.1: Demonstration of conduciveness of phase of an image for edge detection as phase carries more information

Figure 1.1 briefly illustrates the importance of phase of an image. Two images of distinct animals, Zebra and Cheetah are taken and Fourier Transform is performed on them. By taking the magnitude of other image and then performing the Inverse Fourier Transform, the resulting image looks more similar to the input image. This clearly states that phase carries more information about the image. Therefore, for edge detection, transformation on the phase is conducive for detection of edges in the image.

Medical images are very important source of information used for diagnosis, therapy assessment and planning [3]. Some of the very well established image modalities include X-ray, Magnetic Resonance Imaging (MRI), Fluoroscopy, Mammography, Molecular Imaging, Positron Emission Tomography-Computed Tomography (PET-CT) and Computed Tomography (CT). From identifying tumors in lungs, diagnosis of spinal deformity to detection of artery stenosis, medical images play a very important role. In these applications, to deliver fast and accurate diagnosis, image processing techniques such as enhancement and segmentation is employed. To develop automated decision assisting tools which would help in diagnosis, prognosis and screening for health care industry utilization of computational intelligence is also required.

In this thesis, we apply PST to various medical images. We demonstrate the effectiveness of this transform in medical applications by development of first-of-its-kind diagnostic assistant tool for pneumothorax. Machine learning classifier for mammograms based on PST is another application which is an ongoing research work. PST, reported in [1], [2], is orientation and frequency insensitive edge detection algorithm. To broaden application of PST especially for texture segmentation, a orientation and frequency selective PST is under development.

CHAPTER 2

Phase Stretch Transform

Phase Stretch Transform, a physics-inspired approach to detect edges in images, provides paths to explore features of interest of biomedical images [1], [2]. PST is very much related to the time-stretch dispersive Fourier transform [4] , [5] and [6] ,which has led to the discovery of optical rogue waves [7], detection of cancer cells in blood with record sensitivity [8] and best label-free accuracy [9], and optical data compression [10], along with highest performance analog-to-digital conversion [11]. Using the warped group delay dispersion, a time-bandwidth compression of 2.75 times in the warped case is achieved compared to the linear case [12].

In terms of physics, edge detection is essentially result of operation on the image with phase functions with even symmetry, such as quadratic profile [13]. As discussed in Chapter 1, the phase of an image essentially carries more information. With edges being the high frequency margins, a phase profile inserted on the phase of an image to amplify higher frequency content leads to edge detection. This is the principle of PST. A brief description of the procedure governing the operation of PST is described here. The following equation governs the operation of PST in frequency domain to an image $B[x, y]$ where, x and y are two-dimensional spatial variables.

$$A[x, y] = \measuredangle \Big\langle IFFT_2 \Big\{ \widetilde{K}[u, v] \cdot\ \widetilde{L}[u, v] \cdot\ FFT_2 \big\{ B[x, y] \big\} \Big\} \Big\rangle \qquad (2.1)$$

where $A[x, y]$ is the output phase image, $\measuredangle$ is the angle operator, $IFFT_2$ is the two-dimensional Inverse Fast Fourier Transform, FFT_2 is the two-dimensional

Fast Fourier Transform, and u and v are two-dimensional frequency components [1]. The localisation kernel frequency response is given by the function $K[u,v]$ and the warped phase kernel $\phi[u,v]$ is defined by a nonlinear frequency dependent phase as

$$\widetilde{K}[u,v] = e^{j\cdot\phi[u,v]} \tag{2.2}$$

$$\phi[u,v] = \phi_{polar}[r,\theta] = \phi_{polar}[r] \tag{2.3}$$

$$\phi_{polar}[r] = S \cdot \frac{W \cdot r \cdot tan^{-1}\big(W.r\big) - \left(\frac{1}{2}\right) \cdot ln\Big(1 + \big(W \cdot r\big)^2\Big)}{W \cdot r_{max} \cdot tan^{-1}\big(W.r_{max}\big) - \left(\frac{1}{2}\right) \cdot ln\Big(1 + \big(W \cdot r_{max}\big)^2\Big)} \tag{2.4}$$

where $r = \sqrt{u^2 + v^2}$ and $\phi = tan^{-1}\left(\frac{v}{u}\right)$.

By selecting an application-specific phase profile for phase kernel, different frequency components of the input image can be enhanced. In our case, an inverse tangent function as the phase derivative profile is used that enhances high-frequency components.

By controlling the PST parameters, namely, strength S, and warp W, of the phase, along with the width of the Gaussian localization filter and the thresholding values edges in the image can be detected. Due to equalization behavior of PST it gives higher gain to darker area. This is particularly important for its application to chest X-ray where the thin edge of collapsed lung in the dark area becomes visible, otherwise difficult with naked eye.

The above transform is orientation and frequency insensitive. Therefore, it detects all the edges in the image. An orientation and frequency sensitive PST is under developement which selects the edges in particular directions and with particular spatial frequencies. By using a filter function $\chi[r_{selected}, \theta_{selected}]$ applied to the phase profile, the proposed method selectively applies higher phase to desired direction and/or frequency.

For any edge-detection algorithm, one of the promising application is texture segmentation. Using PST, an example to demonstrate texture segmentation is listed here. The statistical feature vector set includes density and standard deviation based on the edge map obtained by applying PST to the input texture image.

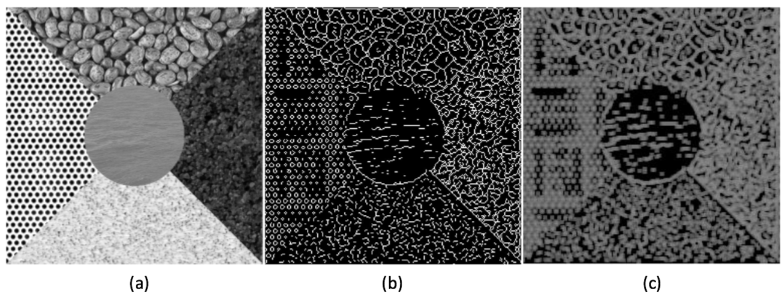


Figure 2.1: An application of PST for texture segmentation on input image with five textures, (a), the resultant edge map using PST (b) and Standard deviation, one of the feature vector using the edge map to use for texture segmentation using K-Means clustering (c).

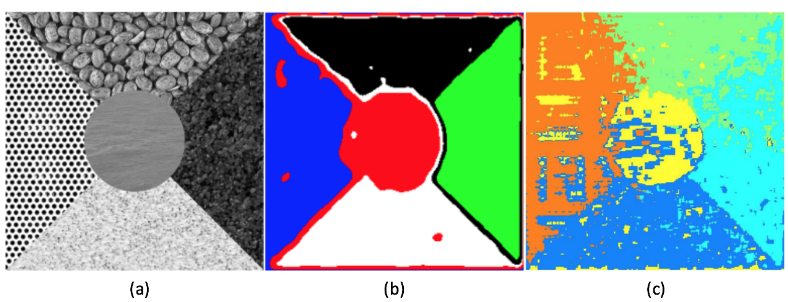


Figure 2.2: An application of PST for texture segmentation on input image with five textures, (a), the resultant texture segmentation using Gabor filter bank (b), a very efficient way to locate the edges and developed texture segmentation using PST demonstrated in (c).

By applying K means clustering on this feature vector set given in Figure 2.1, segmentation of different texture in the input image was achieved. Texture detection with Gabor Filters needs to generate filter banks to cover all the orientations and frequency scaling. In case of images with textures, large Gabor Filter banks are required for segmentation which increases the complexity. A comparison of Gabor Filter with PST is illustrated in Figure 2.2 where a bank of 24 filters that covered 6 orientations and 4 frequency scales [14] was needed for Gabor Filter. On the other hand, with only two statistical features based on edges detected using PST in Figure 2.2, we have shown reasonable texture segmentation. Further, unsupervised hierarchical clustering can also be used to segment textures.

CHAPTER 3

Application of PST to Medical Images

Medical imaging serves as an important source of information for anatomy, organ function along with diagnosis of diseases. The integration of image processing techniques to medical imaging with machine learning methods have led to development of computer-aided diagnostic and decision making tools [15]. These tools have not only performed with a very high accuracy bit also provide real-time analysis of the images for life-critical diagnosis.

PST, which is a physics inspired edge detection algorithm, not only displays features of the image but also, quantify them. In terms of medical and healthcare, PST operation can be associated as visual staining of the images. Therefore, by applying a nonlinear dispersive phase operation PST to medical images [1], [2]. the features in medical images can be enhanced. The resulting edge detection map offers promising application in segmentation and analysis of medical images which is explored here.

In the two examples presented here to illustrates the application of PST for edge detection in biomedical images, images under analysis are Histology Images in Figure 3.1 and Mammograms in Figure 3.2. As evident in the figure, in both examples, the image edges are accurately extracted using PST. Further, the significant variation in the edge detected in class A mammogram and class D mammogram is used to develop feature vector set for developing Machine learning classifier which is under development.

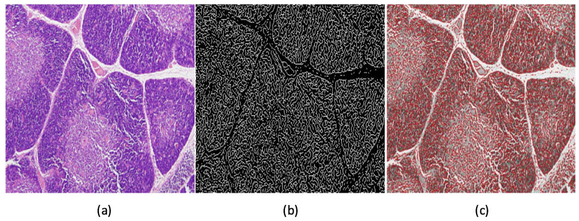


Figure 3.1: An application of PST to histology images, (a) input, (b) Edge detected using PST and (c) Overlay of input images with PST detected edges. S= 0.48 and W =12.14. On this histology image, the cortex and medulla of the thymus are distinct.

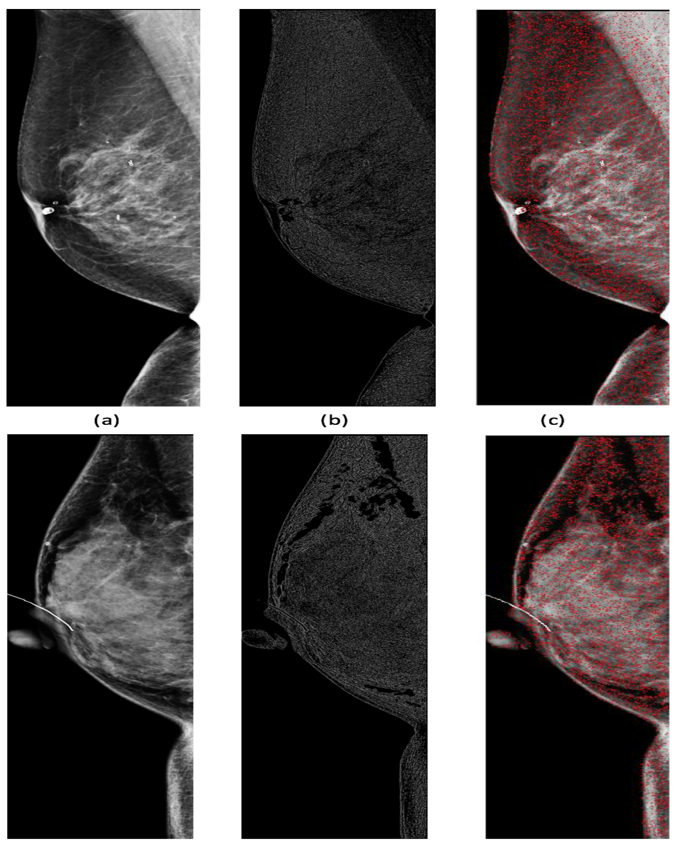


Figure 3.2: PST edge map for Breast of Class A density and Class D density, demonstrates vast variation. (a) and (d) input, (b) and(e) Detected edges using the PST. (c) and (f) Detected edges overlaid with the original image.

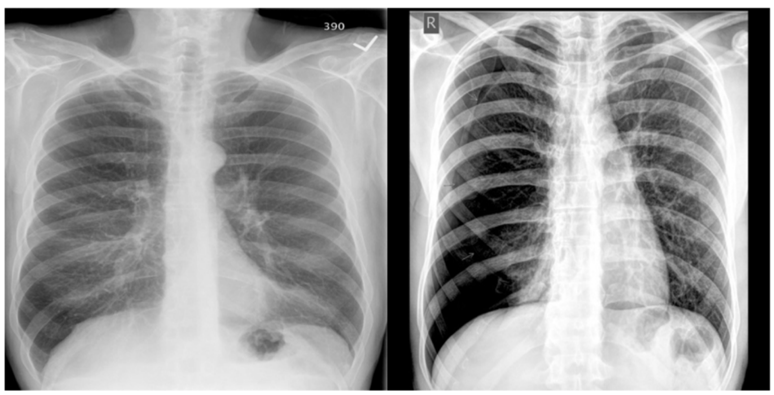
CHAPTER 4

Demonstration of Diagnostic Assistant Tool for Pneumothorax

Pneumothorax is a clinical situation which occurs when air leaks into the space between the lungs and the chest wall. The causes of pneumothorax include primarily a chest injury which penetrates the lung, a lung disease or some kinds of medical procedures. Death caused due to spontaneous pneumothorax is a rare incident but it is observed that it becomes recurrent in patients with smoking habits. An annual mortality rate of 1.26 and 0.62 deaths per million person-years in men and women respectively is seen as reported in [16] using the British statistics. A total recurrence rate of up-to 35 percent is seen with one study of men in the USA [17].

A major contributing factor to mortality caused by pneumothorax is the failure to identify it during an early examination by a radiologist. The reason behind this failure to diagnose pneumothorax is the inability of the radiologist to locate the faint edge of the collapse lung in the chest X-ray which is absent in X-rays of healthy patients. In the following section, we will see that due to the variations in the cases encountered, the collapsed lung is sometime mistaken as the rib boundary and hence, left unnoticed. It is also important to quantify the severity of pneumothorax based on its size before application of any treatment [16]. The diagnostic tool based on PST developed here, provides solution to both the problems. It improves accuracy of time-crucial examination and quantifies the severity.

For developing the diagnostic tool Chest X-rays of patient suffering from pneumothorax are used and compared with healthy ones. The analysis of these images using PST leads to feature enhancement such that patterns that are not visible to human eye can be easily extracted. This forms the basis of application of PST to chest X-ray where the boundary of collapsed lung in pneumothorax is difficult for a radiologist to identify due to the faint contrast variation in the X-ray as seen in Figure 4.1. However, using PST, which enhances even faint transitions in image intensity, the collapsed lung boundary can be easily located.



(a) (b)

Figure 4.1: demonstrates the difficulty to trace the boundary of collapsed lung from the chest X-ray of patient suffering from pneumothorax in (b) compared to chest X-ray of a healthy patient (a).

An important aspect of analysis of Chest X-rays using PST for edge-detection in comparison to conventional Gabor filters is that PST forms a computational approach for edge detection which is orientation insensitive. On the other hand, Gabor filers have directional nature and due to dependence of Gabor filter banks designed for various orientations, they fail to locate the edge of collapsed lung in all the cases encountered. As shown in Figure 4.2, operating Gabor filter banks on X rays designed specifically with certain orientation fail to locate the collapsed lung where as PST covers all orientations and successfully locates the boundary even where the collapse axis is in different directions.

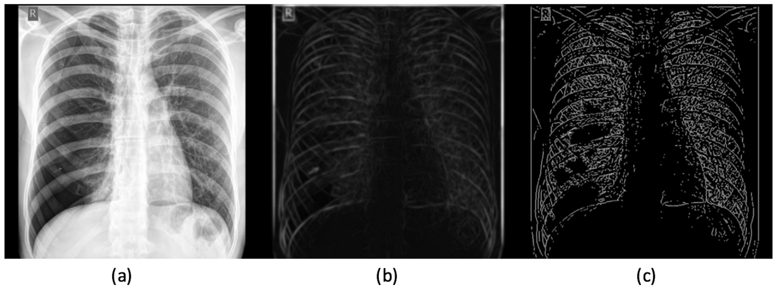


Figure 4.2: The absence of collapse lung boundary in edge map with Gabor filter bank in (b) and its presence in PST (S=0.48, W=12.14) edge map in (c), when operated on the chest X-ray of a patient with pneumothorax (a).

One of the major advantage of applying edge detection algorithm for designing assistant tool for pneumothorax is the absence of collapsed lung in edge map of Normal healthy lungs. This becomes quite clear from the edge maps of healthy X-rays shown in Figure 4.3. The edge map gives the location of ribs and lung, being inflated, does not appear in the PST edge map.

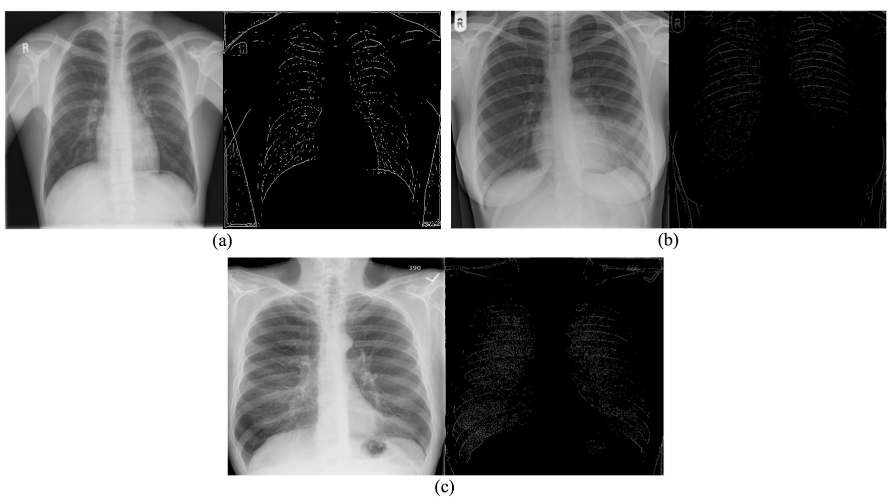


Figure 4.3: Illustrates the absence of collapsed lung edge on application of PST over chest X-ray of three healthy patients (a), (b) and (c) to obtain edge map. Towards the right is the chest Xray and left is edge map obtained using PST with S= 0.48 and W = 12.14.

The three main types of collapsed depicted in Figure 4.4, (a) Partial Collapsed

Lung (Lateral) (b) Partial Collapsed Lung (Top Region) (c) Complete Collapse of Lung, are encountered generally with patients suffering from pneumothorax. Upon application of PST to chest X-ray, the boundary of collapse lung could be identified easily.

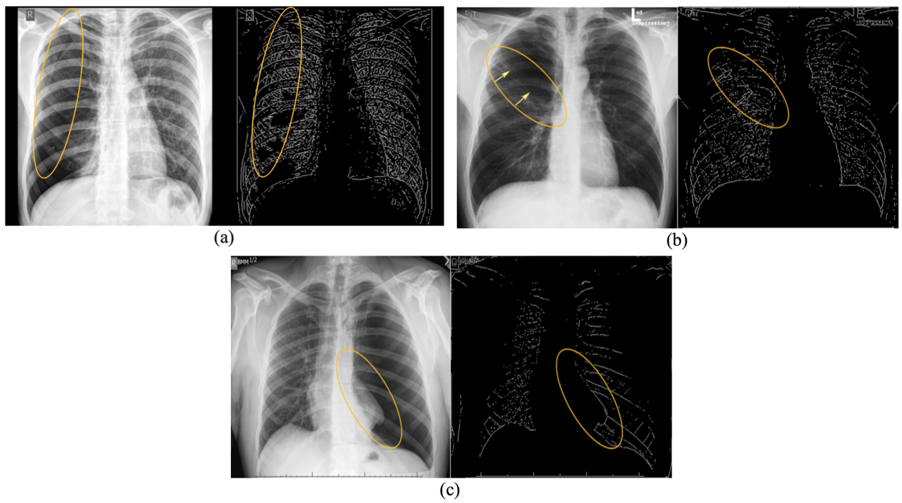


Figure 4.4: Illustrating application of PST as a diagnostic assistance tool for extracting the boundary of collapsed lung using the chest X-rays of patients with pneumothorax. Grayscale chest X-rays of three patients with three different types of medical situations (a) partial lateral collapse, (b) partial top collapse and (c) complete collapse are used for comparison. The yellow circle indicates the location of collapsed lung.

An effort to develop a diagnostic assistant tool for pneumothorax using image processing tools is done for the first time as per our knowledge. By applying further processing steps that involve formation of feature vector set based on the edge map of chest X-ray, an automated boundary detection system for collapsed lung could be developed. Further, as the diagnosis of pneumothorax is a time-sensitive clinical decision, a Web API is under development. This would act as instant decision support system for doctors. The chest X-ray images used for analysis were obtained from web sources. Figure 4.5, uses the case (a) as input and varies PST parameters to obtain edge map that shows the importance of optimization of PST parameters specific to the application.

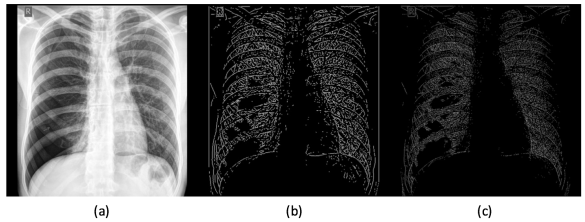


Figure 4.5: Demonstrating the optimization of PST parameters with respect to chest X-ray, (a) Partial collapse of lung, (b) PST edge map with S= 0.48 and W =12.14 and (c) PST edge map with S= 0.4 and W =9. Clearly, a higher warp provides a better visual in the edge map to trace the collapse lung.

With pneumothorax being very common in ventilated critically ill patients, it becomes important to develop such tools for diagnosis as failures in diagnosis can cause life threatening complications [18]. For this, using the principle of anomaly detection, an automated tool PST and deep neural network could be developed which would alarm on encountering an ill patient X-ray. However, this requires access to large database to train the model. Due to limitations of accessing large dataset, this work is not addressed here and left for future application.

CHAPTER 5

Conclusion and Future Work

The thesis demonstrated the use of PST for extracting and enhancing features in biomedical images. In particular, edge detection in chest X-ray helps in tracing the boundary of collapsed lung for a patient with pneumothorax with a higher accuracy which is otherwise difficult for a radiologist to locate with a naked eye. This forms the basis of development of a diagnostic assistance tool to examine chest X-ray images for pneumothorax. A paper covering this research has been submitted in IEEE Summer Topical Series Meeting 2016. The authors are awaiting for the acceptance.

This thesis also covered the implementation of directionality and frequency selectivity behavior for Phase Stretch Transform which opens new applications to explore using PST. For example, with the application of directionality and frequency selectivity of PST, signature patterns of different textures could be designed. A texture segmentation and classification analysis could be performed with PST.

Future work involves developing automated decision making tools for healthcare by extracting features from images using PST and machine learning. With this regard, a Machine Learning Classifier for Mammograms using PST is under development. Apart from the applications discussed above for PST, other areas could also be explored that include document analysis, retina identification, finger print processing etc.

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