Abstract—Due to its convenient real time, non-invasive detection, lung ultrasound is an excellent diagnostic tool in researches related to pulmonary congestion. However, its objective assessment remains elusive. Currently, the detection and evaluation of pulmonary congestion largely rely on manual detection of B-lines by ultrasound specialists. In this paper, I propose an automatic method to detect B-lines. I also examine the correlation between the ratio of B-line occupancy and the brain natriuretic peptide (BNP) values.
Chapter 1

Introduction

Patients with acute heart failure are usually diagnosed to have pulmonary congestion, which happens at the early stage of the syndrome. The syndrome often has a relative long incubation period, during which there is a gradual accumulation of extra-vascular lung water (EVLW), a key to detect heart failure. According to [1], lung ultrasound can be used to exam EVLW.

In [1], the authors manually evaluate lung ultrasound by counting the number of “B-line”. However, this method may not be accurate and time consuming. Two or more thin B-lines can be falsely combined into one wide B-line as B-lines move with the exhaling and inhaling of our lung. Furthermore, the gains of different lung ultra sound videos may be different, one can easily regard noise pattern as a B-line. The aim of this work is to design a new automatic method to detect and evaluate the lung ultrasound.
Chapter 2

Basic concept

2.1 Pleural line and rib

The pleural surface acts as an acoustic reflector that generates the pleural line in ultrasound image. Theoretically pleural line is a thin arch which is the brightest line in the ultrasound image. There are always two ribs adjoining the pleural surface. Rib will absolutely absorb ultrasound, so ribs and the area under the ribs are totally black. When we evaluate the occupancy of B-line, rib spaces should not be considered, as shown in Fig. 1.

Fig. 1  A bright pleural line and two black rib lines with their black rib spaces
2.2 B-line

B-line, which is caused by the ultrasound reflection from tissue with a lot of water, is a vertical, comet-tail artefact arising from the pleural line and spreading up to the edge of screen, as shown in Fig. 2.
2.3 A-line

A-line is just a mirror image of a pleural line, so it always looks like a pleural-line with dark brightness which lies horizontally beneath pleural line. B-line is always brighter than A-line. In that case, once there is an A-line lying on the image, there is no B-line but noise on that column. Sometimes A-line can be very thick, as shown in Fig. 3 and Fig. 4.

![Fig. 3 A-line](image1.png)  ![Fig. 4 Thick A-line](image2.png)

2.4 B-line Detection Guideline

Based on Kenton et al. [2] and Doctor Gabe Rose’s description, B-lines have the following characteristics:

- They are fine reverberation artifacts;
- They originate at the pleural line and extend to the lower edge of the screen having no or very little fading;
- They can’t coexist with A-lines (A-lines are just the repetitions of pleural lines due to the ultrasound, so their brightness is very low. B-lines' brightness is much
higher than A-lines. So, B-lines will absolutely obliterate A-lines;

They move synchronously with pleural sliding.

To detect and evaluate B-lines, we need both spatial and temporal information. The basic idea is to find pleural line firstly; then search the potential B-lines in pleural space (the area under the pleural line); next check the existence of A-lines; use image processing method to eliminate sparse point; finally compute the occupancy of B-lines from the total video.
Chapter 3

Image Pre-processing

In the actual operation, doctors can adjust the gain of probes when generating ultrasound images. The powers of the white noise in different samples are different due to the gain difference, so we need to normalize the samples and eliminate noise before implementing the segmentation methods. In the first section of this chapter, we introduce the fan area locating processing to remove the redundant information out of the ultrasound fan area. The second section focuses on image rectification that transfers the fan-shaped ultrasound image to a standard rectangular image. The last two sections show how to remove white noise, and normalize the ultrasound image to improve the accuracy of my algorithm.

3.1 Fan Area Locating

All the data from Dr.Rose is pre-set to guarantee that the fan areas of ultrasound images are all in the same location. The area out of the fan is totally black. So, it is easy to select the corner points of the fan A, B, C, and D (we can use several frames to make sure they are right). The original frame is shown in Fig. 5.
In the figure FCD is an isosceles triangle, so we can figure out the following solutions:

\[ Y_A = Y_E = Y_B \]
\[ Y_C = Y_G = Y_D \]
\[ X_F = X_E = X_G \]
\[ \frac{Y_F - Y_E}{Y_E - Y_G} = \frac{X_E - X_A}{X_G - X_C} \]
\[ R = d_{DF} \]
\[ r = d_{BF} \]
\[ \alpha = 2\tan^{-1}\left(\frac{d_{AE}}{d_{EF}}\right) \]
All the parameters are listed in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center F</td>
<td>(425,20)</td>
</tr>
<tr>
<td>R</td>
<td>481</td>
</tr>
<tr>
<td>r</td>
<td>51</td>
</tr>
<tr>
<td>α</td>
<td>86</td>
</tr>
</tbody>
</table>

Table 1 Parameters and their values

Using these parameters, we can locate the fan area directly.

### 3.2 Image Rectification

To do the projection along the radial line in the fan-shaped image, we need to transform the fan area to a rectangular area. The outline is shown in Fig. 6.

In Fig. 6, we sample the fan area by the radial lines and then transform them
into a rectangular form. We can adjust the sample rate to approach higher accuracy. In my algorithm, I sample the fan area by every 1 degree and 481 points for every radial line. In that case, I will get an 87X481 (from -43° to 43°) matrix. Using this rectification method will lose the red area of the fan, but it doesn’t matter, because there won’t be anything valuable in this area. Fig. 7 is an example.

Fig.7 An example of rectification
3.3 Denoising

Although ultrasound images can be captured in real-time, low image quality makes it difficult to perform segmentation and identification. Among all the noise, speckle noise and white noise are major causes of image quality degradation. For white noise, it makes the total screen brighter and hard to identify. Fortunately, rib space (the area under ribs) is totally black, so we can measure the mean intensity of white noise by averaging the brightness of the rib space. After that, we can get rid of white noise by subtracting the mean white noise intensity from the original frame. This is shown in Fig. 8.

![Fig.8 The original noisy frame (left) and the denoised frame (right)](image)

For speckle noise, it is inherently generated from mechanism of ultrasound image system and the motion of our body tissue. It is always in the way of A-line detection. In my algorithm, I use time average to deal with them. In Fig. 9, the left is
the original frame, we can see that speckle noise generates a lot of tiny horizontal lines which may be wrongly regarded as A-lines during A-line detection. But after combining several adjacent frames together and taking an average of them, we can easily get rid of it.

![Fig.9 The original noised frame (left) and the denoised frame (right)](image)

### 3.4 Normalizing

Due to the different gains in different videos, it is hard for us to use a constant threshold directly in the upcoming processing. So, we need to normalize every video at first.

Assume that the original brightness of a point is $A$, there are two different gains $G_1$, $G_2$. Then we will get two different outputs $AG_1$ and $AG_2$. In my algorithm, I try to use the brightness of the pleural line (always the brightest area in a frame) as a standard to normalize them. Assuming the brightness of pleural line is $S$, then outputs will be $SG_1$ and $SG_2$. After normalizing, we will get the same answer $\frac{A}{S}$. 
Fig. 10 will give you a direct impression, and the way to locate the pleural line will be discussed in next chapter.

Fig. 10 The first and second pictures are original frames with different gains, the third and fourth pictures are normalized frames. It can be seen that the last two frames’ intensity distributions are not affected by the gain any more.
Chapter 4

Image Segmentation

We follow the guideline that has been discussed before and separate this Chapter into three sections. In the first section, based on some properties of pleural line, we introduce two different methods to determine the location of pleural line. To calculate the ratio of B-lines to rib space, pleural lines' width is used to define the rib space width. In the second section, B-lines are segmented by intensity-based method, and in the last section, for the sake of eliminating the wrong B lines, which contain one or more A-lines, A-line detection is also performed.

4.1 Pleural Line Segmentation

Commonly speaking, pleural line is the brightest area in the thorax ultrasound image, so it seems easy for us to locate it. In practice, however, there are several problems making things harder. First is the instability of probes, this will cause the pleural line moving from frame to frame. Locating pleural line for every frame needs a lot of computation and strongly influences the speed of algorithm. Fortunately, the movement is always very slight, so in my algorithm, I take average on all frames from the whole
video to locate the pleural line. It works well and will be shown in the picture at the end of this chapter.

Second is the number of pleural lines. Generally, for every video, there is always one pleural line located at the middle of the fan area, just between two rib lines. This means that doctors always put the probe between two of our ribs. But sometimes, doctors may put the probe on a rib. In that case, we may see two pleural lines locating at the two sides of the fan area. In my algorithm, it will just locate one of the two pleural lines. Furthermore, Doctor Rose said that this problem is due to the wrong operation of ultrasound technologist, so we only need to focus on videos with one pleural line.

Third is the pattern of the pleural lines. A pleural line is typically a bright thin line in the fan area, but in some of the examples, the brightest areas do not look like a line due to fat and some other tissues as shown in Fig. 11. From the picture, the pleural is at the bottom of the brightest area.

![Fig. 11](image)

Fig. 11 If we just use the total brightest area to decide pleural lines, what we get is the area between red arrows. The correct answer, however, is the area between green arrows.
4.1.1 Region Growing

Region Growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points.

Rolf Adams and Leanne Bischof [3] created a Seeded Region Growing algorithm, which is based on the conventional region growing postulate of similarity of pixels within regions. The algorithm starts from a set of seeds, which also can be treated as a set of regions; then it compares the intensity value along the boundary of each region to the mean intensity value of this region and label the pixel that satisfied a predefined criterion to update the boundary of the region and the mean value of region intensity value; this process is repeated until no new pixels are added to the region labelled. Finally, we can get a region that has similar intensity value. The criterion is defined as that the difference between intensity value of the boundary pixels and the mean value of the region’s intensity is less than a constant threshold $e$.

In my algorithm, I search the max value along the brightest area in Fig. 12 to set the initial seed of growing. And the threshold $e$ is set as 30, Fig. 12 is the result of region growing.
There are two problems for region growing. First, the threshold $e$ is hard to set. In fact, during the test, some of the frames require a small threshold at around 7, but other frames may require a large threshold like 45. So, I can't find a universal threshold for all the frames even after normalization. Second, the solution of region growing does not fit pleural well. Fig.12 is the region growing result of the image in Fig. 11, and, as you can see, the solution of region growing is more likely to regard the red area in Fig.11 as a pleural line rather than the green area.
4.1.2 Intensity-based Local Peak Searching

After getting the rectified image, we compute vertical projection by simply adding the value of each pixel in same column directly. Then, in order to eliminate small gap, dilation and erosion are applied on the projection solution, which is shown in Fig. 13.
In the algorithm, it searches the local peak from 180 to 0, because there won't be a pleural line locating above 200. In fact, they always occur at around $x=100$. The algorithm will pinpoint pleural line by following logic:

The value of the local peak must be larger than the value of the right adjacent point and not less than the value of the left adjacent point.

The value of the local peak must be not less than 90% of the global maximum value.

The algorithm will choose the first local peak meeting the prerequisite from right to left.

For example, my algorithm will locate pleural line at $x=95$ for Fig. 13.

Next, we need to measure the thickness of the pleural line. We choose a relatively strict constraint to get a thin line but not a mass (for example, the result of region growing algorithm). In my algorithm, it searches the value of points from local peak to left and right, until the function is going to increase or the value is less than 90% of the value of the local peak. For the above example, my algorithm comes up with the boundary coordinate [93,104].
Then, we need to detect the width of pleural line. It is similar to the way we depict above, just do projection on the pleural line area ([93,104]) horizontally. What we will get is shown in Fig. 14

![Fig. 14 Projection area and projection result](image)

Combine results on two different directions, we can finally locate pleural line.

Fig. 15 is the solution using the same video of above example.

To compensate for the slight motion of the pleural line, I extend the width of pleural line by 20% (10% for each side, shown in Fig. 16). Assuming the width of B-line is b, the width of pleural line is p. The B-line occupancy should be b/p, but due to the motion of the pleural line, it may hard to totally figure out B-line in a whole video. The algorithm extends p to P=1.2*p to guarantee that it can always figure out B-line completely. After that, we can still approach the real B-line occupancy by 1.2*b/P=b/p. So, this method will only improve the accuracy of my algorithm.
4.2 B-line Detection

After identifying pleural line, we can just detect B-line in pleural space. One direct way is to do projection horizontally and use a threshold to figure out B-lines. But in my algorithm, it only uses the right part of the pleural space to project, shown in Fig. 17. Recall the definition of B-line: a vertical, comet-tail artefact arising from the pleural line and spreading up to the edge of screen, so we won’t lose any
B-line. On the other hand, this method can help my algorithm avoid a lot of strange patterns, like Fig.18, which is very bright at the left part of the pleural space but totally black at right part of the pleural space.

The frames we process have been normalized in the previous step, so we can use a constant threshold to detect B-lines. In my algorithm, the threshold is 64 (25% of the highest value), so it will regard locations with the average intensity higher than 64 as locations of A-line.
4.3 A-line Detection

After we have preliminary detected B-lines, we still need to make sure the existence of A-lines. A-line can locate at the whole area of the pleural space, so we need to check the total area but not the bottom part of the pleural space. Because we just want to make sure there is no A-line lying on detected B-lines, so we just need to exam the existence of A-line on B-line area which has been figured out in the previous section.

Due to the speckle noise (which will cause the projection function having a lot of small gaps) and the variable patterns of A-lines (The width of A-line is unsure, this is shown in Fig. 20), it is difficult to use first order derivative of the projection function to detect A-lines reliably. In my algorithm, it calculates the difference between the base line and the smooth version of projection to detect A-line. Details are shown in Fig. 19.

![Fig. 19 The difference between Smoothed Line and Base Line depicts the location of A-lines accurately](image)
My algorithm uses the following method to smooth the project function. Matrix $Y$ is the input function, matrix $X$ is the smoothed output function, matrix $D$ is derivative matrix and $\lambda$ is a weight parameter. So, the following method tries to minimize the difference between the input and output, as well as the first derivative of the output.

$$\min_X |Y - X|_2 + \lambda |DX|_2$$

$$X = (I + \lambda D^T D)^{-1} D^T Y$$

If the absolute value difference is higher than 0.05, it will be marked as an A-line.
4.4 ABP-line Map Generating

Once we can detect pleural line, A-line and B-line in a single frame, we can apply the algorithm to a whole video and generate a ABP-map, shown in Fig. 21. In the left part of Fig.21, green lines represent the horizontal location and width of pleural line, red area represents the horizontal location and width of B-lines, blue area represents the existence of A-lines. In the right part of Fig. 21, the white area represents the vertical location of A-lines.

To eliminate the accidental mistake, we apply dilation and erosion on blue and red area, solution is shown in Fig. 22.
4.5 B-line Occupancy

After generating ABP-map, we can calculate the ratio of B-line occupancy.

Assuming B is the summation of the value of B-line area (red area without blue line in Fig. 22), A is the total area of the pleural space (the area between green lines), B-line occupancy is equal to $\frac{B}{A}$. 
In this chapter, we discuss the results coming from previous methods. In the first section, we discuss the accuracy of B line detection. Then in second section, we plot B-line occupancy ratio versus BNP value, trying to find a direction relationship between them.

5.1 B-line Detection Results

The algorithm finally produces a new video which marks the area of pleural line, B-line and A-line very well. We now have 48 patients, for each patient we have 8 videos coordinating to 8 different place of their lungs, so we finally get 384 output videos. Fig.23 shows some of the frames from videos. Doctor Rose is satisfied with the accuracy of the algorithm.
5.2 Relationship between BNP value and ratio of B-line occupancy

In order to investigate the relationship between the BNP value and the B-line occupancy ratio, we plot the scatter plot should in Fig.24. From the plot, we can’t find any valuable relationship between the two parameters. First is the limitation of the data set, we just have 48 patients, for each patient we have 8 videos coordinating to 8 different places of lungs. We using the average ratio of the 8 videos to evaluate the B-line occupancy of every patient. Second is about the BNP value. Doctor Rose admits that there could be numerous of reasons which could influence the value of BNP. So, the result we get from Fig. 24 is reasonable.
Chapter 6

Summary and Future works

This work provides a method to detect and evaluate the B-lines in thorax ultrasound images. The detection results correlate quite well with those by clinicians. The work also proves that there isn’t any direct relationship between BNP and ratio of B-line occupancy. All these solutions are confirmed by Doctor Rose.

In the next stage, we plan to get some new data sets to evaluate correlation between B-line occupancy and EVLW. This can strongly prove the practicability of my algorithm.
References

