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Automatic Extraction of Diaphragm Motion and Respiratory Pattern from Time-sequential Thoracic MRI

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Abstract

Thoracic time-sequential MRI can be used to assess diaphragm motion pattern without exposing radiation to subject. Clinicians may employ the motion to evaluate the severeness of chronic obstructive pulmonary disease (COPD). This study proposed a novel method of diaphragm motion extraction method on time-sequential thoracic MRI in sagittal plane. Otsu's threshold and active contour algorithm are used to obtain diaphragm boundary. An automatic diaphragm motion tracking and extraction of respiratory pattern are also performed based on the diaphragm boundary. A total of 1200 frames time-sequential MRI in sagittal plane was obtained for total of 15 subjects (8 healthy volunteers and 7 COPD patients). The proposed method successfully extracts diaphragm motion and respiratory patterns for both healthy volunteers and COPD patients.

Keywords: magnetic resonance imaging, chronic obstructive pulmonary disease, respiratory pattern, diaphragm motion

1. Introduction

Diaphragm is a dome-shape respiratory organ located below the lung that separates chest from the abdomen. It controls the movement of the lungs and the breathing process (inhalation and exhalation). The motion of the diaphragm can be used to evaluate the severeness of chronic obstructive pulmonary disease (COPD) [1]. Hence, in the past few decades diaphragm motion has been assessed in several studies [1-6]. In 1985, Diament et al. [2] extracted diaphragm motion from ultrasonography to evaluate diaphragm motion abnormalities. Gerscovich et al. [3] and Boussuges et al. [4] used M-mode ultrasonography to record diaphragm motion in two dimensions. Despite its portability, real-time examination and no ionization radiation, due to the nature of ultrasonography the imaging result does not reveal tissue density and potentially creates artifacts. The use of magnetic resonance imaging, which provides more clear and detailed images of soft tissue, has been proposed in [5-7]. However, none of them use automatic extraction to extract diaphragm motion and its respiratory pattern.

In this study, we focused on automatic extraction of diaphragm motion from a time-sequential thoracic MRI in sagittal plane. The extraction was performed to 15 subjects (8 healthy volunteers and 7 COPD patients). We then compared the statistical analysis of the diaphragm motion extracted from healthy volunteers and COPD patients.

2. Subjects and Methods

This section describes the image acquisition and the methods of automatic diaphragm motion extraction including respiratory pattern extraction.

2.1. Image Acquisition

The MR images were acquired using 1.5T INTERA ACHIVA nova-dual (Philips Medical Systems) whole-body scanner with a 16ch SENSE TORSO XL Coil. A 2D balanced FFE sequence was used. The imaging parameters are as follow. SENSE factor: 2.2, flip angle: $45°$, TR: 2.2ms, TE: 0.9ms, FOV: 384mm, in-plane resolution 256x256 pixels and $1.5x1.5mm^2$, slice thickness: 7.5mm, slice gap=6.0mm, scan time: 150ms/frame.

Normal breathing was instructed for all subjects during the acquisition process and total of 1200 frames in sagittal plane were obtained for each subject. Image acquisition experiment was conducted under an approval of Ethical Review Board of Chiba University.

2.2. Diaphragm Motion Extraction

In order to get diaphragm motion, we first define a region of interest (ROI) of the MR image by cropping the image that covers the diaphragm boundary. Typically, diaphragm boundary is located in middle of MRI in sagittal plane. To cover the whole area of diaphragm boundary, we first define two parameters, w and h to represent the width and height of ROI.

There are two main steps to extract diaphragm motion. The first step is to obtain diaphragm boundary for the first frame only using active contour algorithm. Once the first frame of diaphragm boundary is obtained, the next step is to extract the diaphragm boundary for the subsequent frames based on normalized cross correlation (NCC) value. The complete processes of diaphragm motion extraction are as follows.

We first perform clustering-based image thresholding using Otsu's thresholding method [8]. After the thresholding process, the diaphragm area became clearly distinguishable from other organs. A mask is created above the diaphragm boundary as seed point in order to trace the diaphragm boundary using active contour algorithm [9]. An optimization of the diaphragm boundary detection can also be optimized using a method proposed by Alfiansyah [10] or [11]. Note that this process is only performed for the first frame only. Figure 1 shows the process of obtaining diaphragm boundary of the first frame.

Set ROI for the first frame   Otsu Threshold   Active countor algorithm
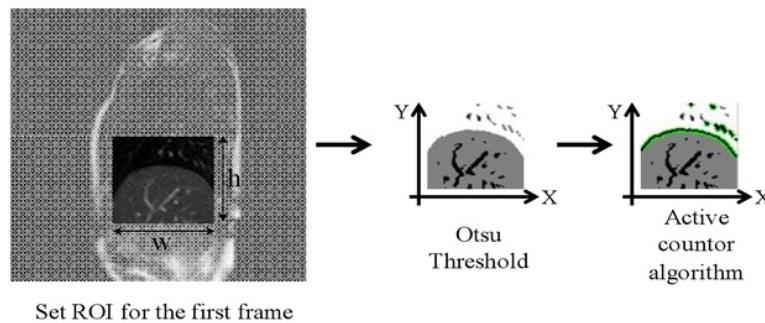
Figure 1. Obtaining diaphragm boundary for the first frame

To get diaphragm boundary for the subsequent frames, we utilize one column matrices template defined by T_x where $x=1..w$. The element of matrix T_x is obtained from pixel values of the ROI at column the x. Therefore, the size of matrix T_x is $1 x h$, where h is the height of the ROI. It is also necessary to generate a 2D spatio temporal of column x (Figure 2(a)). The location of diaphragm boundary at column x for the subsequent frames is defined by the highest NCC value between the matrix T_x and the 2D spatio temporal of the subsequent frames at column x. The process is repeated for $x=1..w$. We denoted the position of the diaphragm boundary at location x as $f_x(i)$ where i represents the ith frame. The $f_x(i)$ shows periodic peaks and valleys associated with respiration cycles. Figure 2 illustrates how to determine the location of diaphragm boundary.
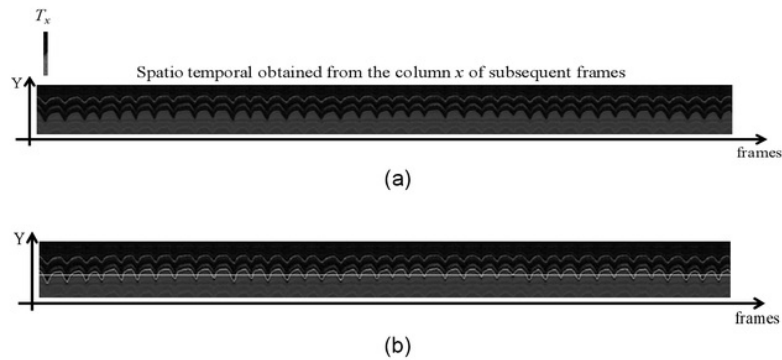
(a)

(b)

Figure 2. Determine the location of diaphragm boundary. (a) Element of matrix Tx is obtained from the pixel values of ROI at column x and the spatio temporal is generated at the column x from the subsequent frames; (b) The detected diaphragm motion at column x (fx(i)), is represented by the white line

2.3. Respiratory Patterns Extraction

Respiratory patterns are automatically extracted from diaphragm motion that is previously obtained. The extraction of respiratory patterns is only performed at the column x that has the largest diaphragm movement.
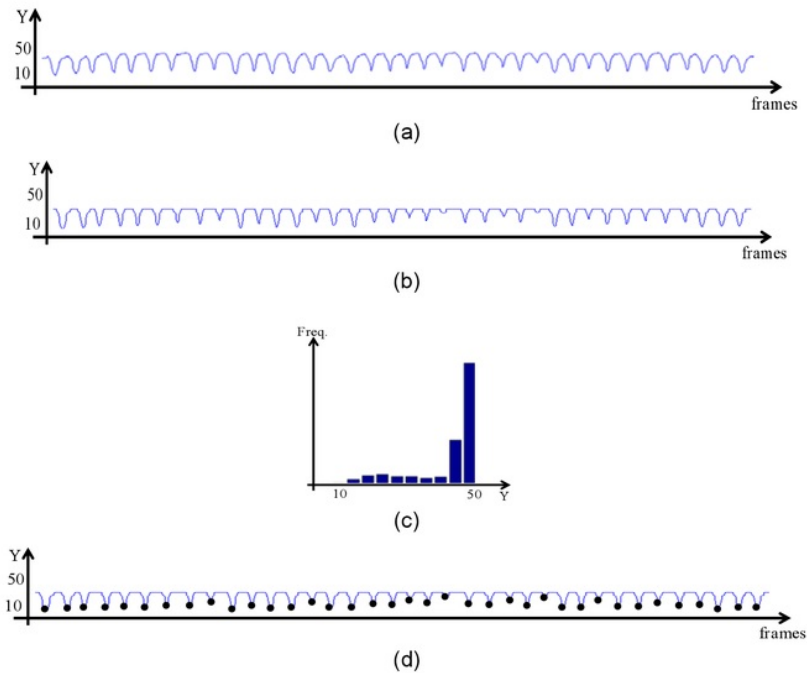

(a)

(b)

(c)

(d)

Figure 3. Determining peaks from a signal. (a) Original signal before noise removal. (b) Signal after noise removal using an adaptive noise-removal filter. (c) Histogram of respiratory signal after noise removal; baseline is determined by most occurring value. Points that are higher than baseline multiplied a parameter p are marked as peak. (d) Valleys are detected using regional minima. The detected valleys are circled

In general, a respiratory pattern consists of one peak and one valley. A semi-automatically peak and valley detection was proposed in [12]. Although this proposed method was able to detect peaks and valleys from a respiratory pattern, the respiratory signal is not obtained from time-sequential images. It is directly measured by a digital voltage signal using a pressure sensor. Moreover, manual user review is also required to verify the results.

In this study we propose an automatic peak and valley detection from respiratory signal obtained from diaphragm motion (Figure 3). We first perform noise filtering using an adaptive noise-removal filter. Next step is to set a baseline value based on the statistical mode (most frequently occurring value) of the signal. A parameter, p is used to determine the height of the peak. Points in the respiratory signal that are higher than the baseline multiplied with p are marked as peak. The similar process is also done to detect the valleys. Instead of finding statistical mode, regional minima of the signal are calculated and multiplied by a parameter, v. All points below this value are marked as valley.

3. Results

We tested the proposed method to a total of 15 subjects (8 healthy volunteers and 7 COPD patients). The number of frame for each subject is 1200 frames. Table 1 shows the number of respiratory patterns found and the number frame for one respiratory cycle.

Table 1. Number of respiratory patterns found and the average number of frame required for one respiratory cycle in healthy volunteers

Subject	# Resp. Pat.	#Frame/cycle
Healthy Volunteers		
1	32	36.7
2	36	33.3
3	37	32.4
4	52	23.1
5	19	63.2
6	57	21.0
7	48	25.0
8	34	35.3
COPD patients		
1	49	24.5
2	77	15.6
3	34	35.3
4	38	31.6
5	61	19.7
6	56	21.4
7	46	26.1

Ideally, the number of frame for one respiratory cycle ranges from 25-35 frame/cycle. Figure 4 shows an example of respiratory patterns which successfully extracted from healthy volunteer #3. The number of detected respiratory patterns is 37 and the number of frame per cycle is 32.4 which is considered as normal respiratory motion.
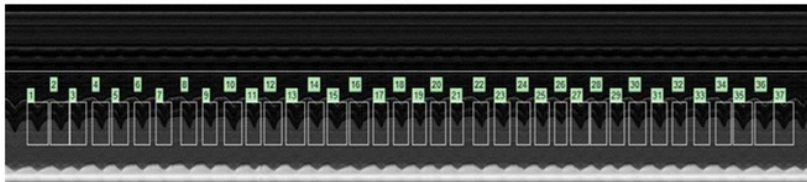

Figure 4. Detected respiratory patterns for healthy volunteer #3

However, breathing irregularity is a factor that makes respiratory pattern extraction failed. Another factor that affects the number of detected respiratory pattern is respiratory frequency. For example, subject 6 has the largest number of extracted respiratory patterns among the other healthy volunteers. The subject's 2D spatio temporal shows that this subject has high respiratory frequency (Figure 5(a)).

The healthy volunteer who has the smallest number of detected respiratory patterns is subject 5. As we can see in the Figure 5(b), subject 5 has several irregular breathing cycles (pointed by white arrows) that make the system failed to extract them.
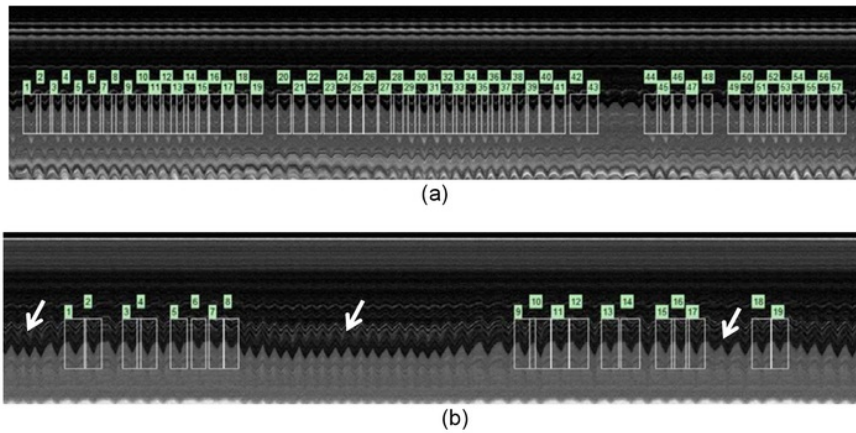

(a)

(b)

Figure 5. An example of (a) high respiratory frequency and (b) irregular breathing of healthy volunteers

For COPD patients, the number of extracted respiratory patterns tends to be higher compared with healthy volunteers. Figure 6 shows two examples of COPD patients 5 and 6. The frame/cycle of these patients are 19.7 and 21.4, respectively. It indicates that these patients have smaller lung volume capacity compared with healthy subjects. Several irregular breathings were also found in the first 100 frames of the patient 6 (Figure 6(b)) and they failed to be extracted.
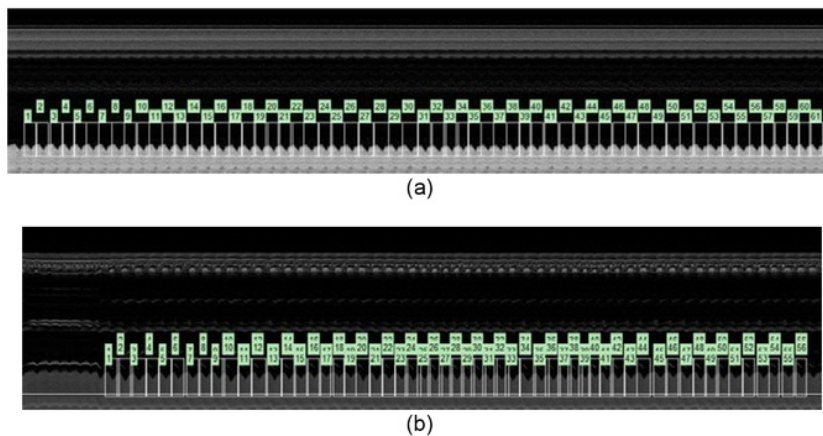

(a)

(b)

Figure 6. Two examples of extracted respiratory patterns of COPD patient 5 and 6

4. Conclusion

This study proposed an automatic method to extract diaphragm motion and respiratory patterns from time sequential MR images in sagittal plane. Our method successfully extracts diaphragm motion and respiratory patterns for both healthy volunteers and COPD patients. However, our study has certain limitations. First, it fails to detect irregular breathing patterns which can occur during MRI acquisition. Second, the results of the present study were obtained from a small number of subjects. Larger number of subjects for both healthy volunteer and COPD patients are required to validate our method.

Acknowledgements

References

[1] Shibata H, Iwasawa T, Gotoh T, Kagei S, Shinohara T, Ogura T, Inoue T. Automatic Tracking of the Respiratory Motion of Lung Parenchyma on Dynamic Magnetic Resonance Imaging: Comparison With Pulmonary Function Tests in Patients With Chronic Obstructive Pulmonary Disease. *Journal of thoracic imaging*. 2012; 27(6): 387-392.

[2] Diament MJ, Boechat MI, Kangarloo H. Real-time sector ultrasound in the evaluation of suspected abnormalities of diaphragmatic motion. *Journal of clinical ultrasound*. 1985; 13(8): 539-543.

[3] Gerscovich EO, Cronan M, McGahan JP, Jain K, Jones CD, McDonald C. Ultrasonographic evaluation of diaphragmatic motion. *Journal of ultrasound in medicine*. 2001; 20(6): 597-604.

[4] Boussuges A, Gole Y, Blanc P. Diaphragmatic motion studied by m-mode ultrasonography. *Chest*. 2009; 135: 391-400.

[5] Kotani T, Minami S, Takahashi K, Isobe K, Nakata Y, Takaso M, Moriya H. An analysis of chest wall and diaphragm motions in patients with idiopathic scoliosis using dynamic breathing MRI. *Spine*. 2004; 29(3): 298-302.

[6] Kolar P, Neuwirth J, Sanda J, Suchanek V, Svata Z, Volejnik J, Pivec M. Analysis of diaphragm movement during tidal breathing and during its activation while breath holding using MRI synchronized with spirometry. *Physiological Research*. 2009; 58(3): 383.

[7] Iwasawa T, Takahashi H, Ogura T, Asakura A, Gotoh T, Shibata H, Inoue T. Influence of the distribution of emphysema on diaphragmatic motion in patients with chronic obstructive pulmonary disease. *Japanese journal of radiology*. 2011; 29(4): 256-264.

[8] Otsu N. A threshold selection method from gray-level histograms. *Automatica*. 1975; 11(285-296): 23-27.

[9] Chan TF, Vese LA. Active contours without edges. Image Processing, *IEEE Transactions*. 2001; 10(2): 266-277.

[10] Alfiansyah A. A Unified Energy Approach for B-Spline Snake in Medical Image Segmentation. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2010; 8(2): 175-186.

[11] Tjandrasa H, Wijayanti A, Suciati N. Segmentation of the retinal optic nerve head using Hough transform and active contour models. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(3): 531-536.

[12] Lu W, Nystrom MM, Parikh PJ, Fooshee DR, Hubenschmidt JP, Bradley JD, Low DA. A semi-automatic method for peak and valley detection in free-breathing respiratory waveforms. *Med. Phys.* 2006; 333634(6).

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1 Swastika, Windra, Yoshitada Masuda, Naoko Kawata, Koji Matsumoto, Toshio Suzuki, Ken Iesato, Yuji Tada, Toshihiko Sugiura, Nobuhiro Tanabe, Koichiro Tatsumi, Takashi Ohnishi, and Hideaki Haneishi. "Evaluation of COPD's diaphragm motion extracted from 4D-MRI", Medical Imaging 2015 Image Processing, 2015.
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12 Hirofumi Shibata, Tae Iwasawa, Toshiyuki Gotoh, Seiichiro Kagei et al. "Automatic Tracking of the Respiratory Motion of Lung Parenchyma on Dynamic Magnetic Resonance Imaging", Journal of Thoracic Imaging, 2012
Publication

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