Breath Sound Distribution Images of Patients With Pneumonia and Pleural Effusion

Ram Mor MD, Igal Kushnir MD, Jean-Jacques Meyer MD, Joseph Ekstein MD,
and Issahar Ben-Dov MD

OBJECTIVE: To determine whether breath sound distribution maps can differentiate between patients with pneumonia or pleural effusion versus healthy controls. METHODS: We recorded breath sounds from 20 patients conventionally diagnosed as having pleural effusion, 20 patients conventionally diagnosed as having pneumonia, and 60 healthy controls, of whom 20 served as a learning sample. All subjects were examined with a computer-based multi-sensor breath sound mapping device that records, analyzes, and displays a dynamic map of breath sound distribution. The physicians who interpreted the breath sound images were first trained in identifying common characteristics of the images from the learning sample of normals. Then the images from the 40 patients and the 40 controls were interpreted as either normal or abnormal. RESULTS: In the normal images, the left and right lung images developed synchronously and had similar size, shape, and intensity. The sensitivity and specificity of blinded differentiation between normal and abnormal images when the physician interpreter did not know the patient's workup were 82.5% and 80%, respectively. The sensitivity and specificity of blinded detection of normal and abnormal images when the interpreter did know the patient's workup were 90% and 88%, respectively. CONCLUSIONS: Computerized dynamic imaging of breath sounds is a sensitive and specific tool for distinguishing pneumonia or pleural effusion from normal lungs. The role of computerized breath sound analysis for diagnosis and monitoring of lung diseases needs further evaluation. *Key words: acoustics, breath sounds, lung sounds, respiratory sounds, pneumonia, pleural effusion, imaging, mapping.* [Respir Care 2007;52(12):1753–1760. © 2007 Daedalus Enterprises]

Introduction

Medical history and physical examination are standard procedures for evaluating patients with respiratory symptoms.[1-3] Auscultation with a stethoscope contributes much to the physical examination, but it is limited to a narrow range of lung sounds and relies highly on the examiner's skills.[3,4] Moreover, other studies have shown that the diagnostic accuracy and value of the stethoscope are questionable.[5] Thus, technologically based examinations such as laboratory tests and imaging studies are frequently carried out for further clarification and elucidation of the patient's clinical status.[2,6,7] Previous reports presented the advancement in lung sound analysis from human-based auscultation to a computer-based analysis tool that allows more objective, accurate, and measurable results.[4,8-12] The results of such computerized analyses have the added advantage of easily comprehensible visual displays that can

be archived for follow-up.[3,11,13–15] Sound analysis is also safer than radiologic examinations, which carry potential risk to the patient and operator.[16]

Murphy et al[11] compared 50 subjects diagnosed as having pneumonia to 50 healthy controls, and demonstrated that detection of automated adventitious lung sounds (ie, crackles and rhonchi) had a sensitivity of 0.78 and a specificity of 0.88. Breath sounds are another measurable component of lung sounds.[17] Normal breath sounds have distinctive characteristics, such as higher sound intensity during inspiration than during expiration[12,18] and progression from apex to base.[12,19] Abnormal breath sounds also have distinctive characteristics, including overall or localized reduction in intensity, which may occur in pneumonia,[7,20] or may be the result of sound transmission being impaired by pleural effusion.[6] Furthermore, studies have demonstrated that normal breath sound measurements are distinguishable from abnormal ones, and have potential as a tool for detecting lung disease.[10,21–23]

Breath sounds can be displayed as a numeric graph[22] or as a map of breath sound distribution, either as amplitude contour maps[8,18] or as grayscale sound intensity maps.[10,12] Breath sound distribution data are created from multiple signals that are simultaneously captured from the lungs and can be viewed as multiple graphs or as a breath sound distribution map. Such maps may enable visualization of normal and abnormal breath sound characteristics that can be interpreted for insight into the spatial distribution of breath sound intensity, which makes them well suited for clinical applications.

We used a computer-based multisensor breath sound mapping device that records, analyzes, and presents breath sound distribution as a function of time in a dynamic grayscale map. We evaluated whether a trained reader of such maps (images) can accurately distinguish between normal and abnormal breath sounds in patients with pneumonia or pleural effusion versus healthy controls.

Methods

Study participants were enrolled from 3 Israeli health services (Clalit Health Service, Ramat-Gan, Israel; Clalit Health Service, Haifa, Israel; and Maccabi Health Service, Ra'anana, Israel) and one medical center (Sheba Medical Center, Tel Hashomer, Israel). The study was conducted according to the ethical standards of the World Medicine Association Declaration of Helsinki, and approved by the institutional review boards of each participating center. Informed consent was obtained from each participant prior to inclusion in the study.

The study cohort consisted of 40 patients who were diagnosed with lung disease (mean ± SD age 56 ± 17 y,

45% female) of whom 20 were diagnosed as having pneumonia and 20 were diagnosed as having pleural effusion. We also recruited 60 healthy subjects who were referred for routine chest radiograph for employment requirements (mean ± SD age 57 ± 15 y, 38% female). Of these 60 subjects, the first 20 were studied as a learning sample, and the following 40 as controls. Individuals included in the study were considered healthy if they were nonsmokers with no history of lung disease and had normal physical examination and normal posteroanterior and lateral chest radiograph. Patients were included if they had a body mass index < 35 kg/m², height of 160–195 cm and had radiographically and clinically confirmed diagnosis of pneumonia or pleural effusion. Subjects were excluded for chest cage deformation, excessive hirsutism, or potentially contagious skin lesions. Initial patient diagnosis of pneumonia or pleural effusion was determined by the treating physician, the diagnosis was based on physical examination, stethoscope auscultation, and radiographic findings. The radiographic findings were determined by a board-certified radiologist from each participating center. The radiographic findings were confirmed by 2 blinded radiologists. The treating physician's diagnosis was confirmed by a pulmonologist, according to accepted criteria for diagnosing pneumonia,[2,24] pleural effusion,[25] and healthy lungs.

All subjects were examined with the Vibration Response Imaging device (Deep Breeze Ltd, Or Akiva, Israel), which has Conformité Européenne (European health and safety product label) approval (certificate 3414GB410050915) and Israel Health Institution approval (certificate 1102000) as a lung diagnostic device. This device uses 40 contact sensors (Meditron, Oslo, Norway) with a linear frequency response of ± 2 dB in the frequency range 50–400 Hz. The sensors are assembled on 2 planar arrays, which are designed to cover the posterior lung area (Fig. 1). The sensors are coupled to the subject's back by a computer-controlled low-suction vacuum, according to the following guidelines:

1. The upper row of each sensor array is placed approximately 2 cm above the scapula.

2. The inner sensors of the upper rows are placed approximately 5 cm from the vertebral column.

3. The bottom row of the 2 sensor arrays is located at approximately the same height (within 1 cm).

4. The 2 sensor arrays are aligned parallel along the vertebral column.

The subjects were instructed to breath deeper than normal through an open mouth during a 12-second recording (3 or 4 respiratory cycles). No forced exhalation or other breathing maneuvers were performed. Recordings were carried out in a quiet but not soundproof room.

Fig. 1. Placement of the sensor array. Low-pressure vacuum attaches the sensors to the skin.

The captured lung sound signals were band-pass filtered (150–250 Hz), which allowed only the desired frequency range of breath sounds.[19] The signals were processed and the breath sound distribution was displayed as a 2-dimensional dynamic grayscale image with 256 gray levels (Fig. 2). Areas where the lung vibration energy is highest appear in black, and areas where the lung vibration energy is lowest appear in light gray. The minimum data area is defined as white.

For the creation of the dynamic grayscale map, the filtered signal from each sensor is down-sampled to produce an envelope signal. These envelope signals were then converted into a logarithmic scale with the following algorithm:

A: Refer to the back as an XY plane and let

$EVP(x_i, y_i, t)$ $(1 \leq i \leq$ number of sensors, $0 \leq t \leq T)$
represent the envelope (EVP) sample t of the sensor located on the back at (x_i, y_i).

B: For each time slot t, the system assembles a plane in which the (x_i, y_i) position equals $EVP(x_i, y_i, t)$.

C: Since the positions of the sensors are discrete, a 2-dimensional interpolation is exercised, using a Gaussian interpolator.

The grayscale coded dynamic image of the lungs is created from a series of planes; each plane represents the breath sound distribution during 0.17 s of recording.

Image Analysis

All images were displayed on a 43-cm liquid crystal display monitor (FlexScan L568-BK, Eizo, Nanao, Japan), calibrated with grayscale calibration software (AccuGray, Sencore, Sioux Falls, South Dakota) and color and luminance analysis sensors (ColorPro, Sencore, Sioux Falls, South Dakota) to achieve compliance with the Digital Imaging and Communications in Medicine (DICOM) part 14 specifications. They were evaluated separately by the 2 readers who were qualified physicians (one pulmonologist and one general practitioner) who underwent 4 hours of training in image interpretation by analyzing the 20 healthy learning sample images. The training was conducted by showing to the readers (separately) the dynamic images sequentially and working with them to establish their ability to distinguish 4 basic characteristics that were identified in the learning sample (see Fig. 2):

1. Similar distribution of grayscale intensity between the left and right lung images during the inspiratory phase
2. Synchronization of the progression of breath sound distribution between the left and right lung images along the inspiration phase
3. Similar shape and size (area) of the left and right lung images at the peak intensity of inspiration (approximately at 50% of inspiration)[26]
4. Higher grayscale intensity during inspiration than during expiration

After the training session the readers blindly analyzed the remaining 80 images in a random order, without any previous knowledge of the number of images obtained from the patients or the healthy controls. Cross-sectional analysis was performed by reading the images in 2 phases. In the first phase the readers evaluated randomized images without having any of the subject's clinical information except age, sex, height, and weight. In the second phase the readers analyzed re-randomized images of patients whose workup results (excluding chest radiograph findings) were at hand. The final assessment of "normal" or "abnormal" images was determined by consensus between the 2 analysts, but in case of disagreement the "abnormal" result was accepted. The results of each phase of the image analysis were compared to the patient's clinical diagnosis.

Statistical Analysis

Analysis of data was performed with statistics software (SPSS 11.5.1, SPSS, Chicago, Illinois). Means and percentages of all case report variables were tabulated and are presented as mean $\pm$ SD. Statistical tests were performed on a 0.05 level of significance. Continuous variables were compared between groups with a 2-sample t test. Nominal
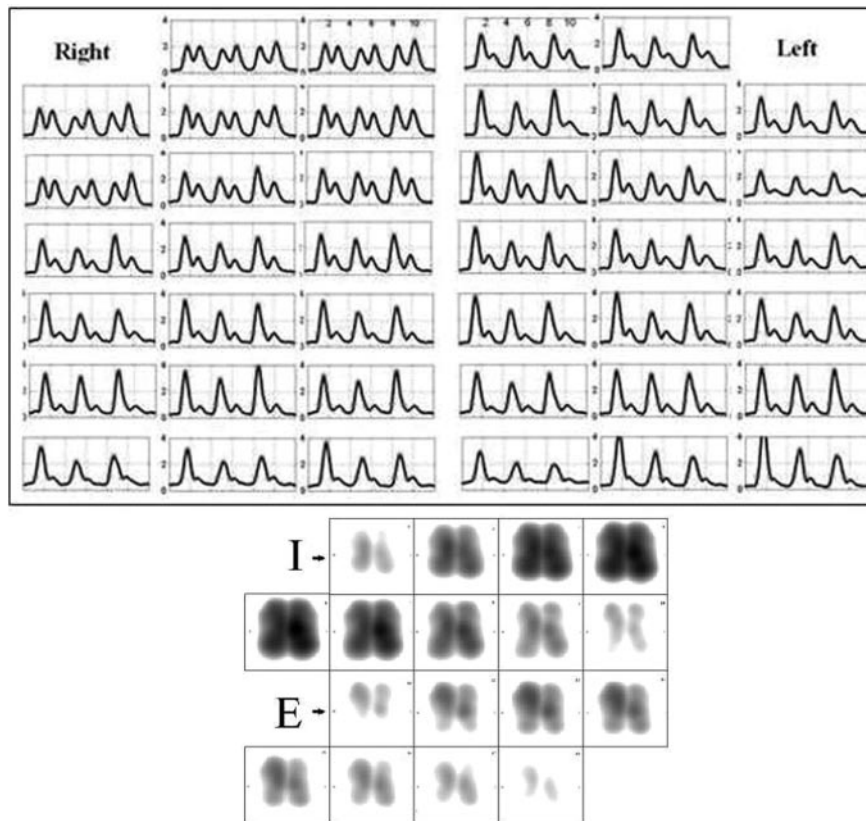
Fig. 2. Lung sound signals and images from a healthy subject. Left panel: Signals of acoustic intensity from the 40 sensors, according to their locations. These signals are of the total recording post-filtering and of an envelope creation. Right panel:Grayscale sequence of 0.17-s frames of breath sound distribution maps of one breathing cycle from the same healthy subject. "I" indicates the start of inspiration. "E" indicates the start of expiration. These frames when presented sequentially constitute the dynamic image.

variables were compared between groups with the Fisher exact test. Sensitivity and specificity for the detection of normal and abnormal breath sound images were calculated by comparing the 2 readers' evaluations to the patient's diagnosis. Inter-observer agreement for image interpretation was assessed with the kappa statistic, which was scored as follows: < 0.40 indicated positive but poor agreement, 0.41–0.75 indicated good agreement, 0.76–0.99 indicated excellent agreement, and 1.00 indicated complete agreement.[27]

Results

There was no significant difference between the 40 healthy controls and 40 pulmonary patients with regard to all the examined demographic and anthropometric variables (Table 1). The consensus between the 2 readers' image analyses without the patient's workup was 81%, and with the workup it was 94%. The images in the study group that were judged "normal" by the readers had image characteristics similar to the healthy subjects in the learning sample: the left and right lungs had similar distribution of intensity and synchronized development during the inspiratory phase, as well as similar shape and size in the peak inspiratory frame (at approximately 50% of inspiration), and the intensity of the inspiratory image was higher than the expiratory image (see Fig. 2).

There was no significant difference between the breath sound image assessment of "abnormal" or "normal" for patients diagnosed as having pleural effusion and patients diagnosed as having pneumonia (by Fisher's exact test, $p = 0.09$ without patient workup, and 0.60 with patient workup). The sensitivity and specificity of detecting normal and abnormal images without awareness of patient workup were 82.5% and 80%, respectively, whereas these values increased to 90% and 88%, respectively (Table 2), with knowledge of the patient workup.

Figure 3 shows a multiple graph view and image of the breath sound distribution of a 54-year-old female diagnosed as having pleural effusion; the figure demonstrates a localized missing area that corresponds to the location of the effusion. Figure 4 shows a multiple graph view and an image of the breath sound distribution of a 36-year-old male diagnosed as having lobar

Table 1.   Demographic and Anthropometric Characteristics of the Healthy Controls and Patients

	Controls (n = 40)		Patients (n = 40)		p*
	Mean ± SD	Range	Mean ± SD	Range	
Age (y)	57 ± 15	20–80	56 ± 17	18–82	0.80
Sex (F, M)	18, 22	NA	15, 25	NA	0.50
Weight (kg)	78.3 ± 14.1	51–123	76.4 ± 17.7	51–120	0.61
Height (cm)	170.9 ± 7.9	155–185	169.3 ± 8.3	155–196	0.39
BMI (kg/m^2)	26.7 ± 3.6	18.0–35.9	26.6 ± 5.6	17.6 – 40.1	0.93

* Via t test for unpaired data
NA = not applicable
BMI = body mass index

Table 2.   Sensitivity and Specificity of the Classification of Lung Sound Images as Normal or Abnormal

	Image vs Patient Diagnosis	Image Plus Patient Workup vs Patient Diagnosis
True negative (n)	32	35
True positive (n)	33	36
False negative (n)	7	4
False positive (n)	8	5
Sensitivity (%)	82.5	90.0
Specificity (%)	80.0	87.5
Kappa statistic	0.63	0.78
95% confidence interval	0.61–0.64	0.76 to 0.79

pneumonia; the figure demonstrates nonsynchronized development of the image and late appearance of hyperintensity in the inspiratory phase.

A subgroup analysis was also performed for the detection of "normal" and "abnormal" images. The subgroup analysis was done by focusing on the healthy group (n = 40) and on each of the pathological groups (pneumonia n = 20, pleural effusion n = 20). The statistical analysis was similar to the one performed for the general analysis. The subgroup analysis of patients diagnosed as having pleural effusion had a sensitivity of 95% and a specificity of 88%, with and without patient workup. The subgroup analysis of patients diagnosed as having pneumonia had a sensitivity of 70% and a specificity of 80%, without patient workup, which rose to a sensitivity of 85% and a specificity of 88% with patient workup. In 5 of the overall cases a repeat recording was necessary because of identification of artifacts in the image.

Discussion

Attempts to utilize computerized recordings of lung sounds as an aid for diagnosis and education have been previously described, with various success and complexity of systems. In the present study we showed that by using dynamic breath sound distribution images, the readers could easily and with good accuracy differentiate between normal and abnormal images from healthy and nonhealthy persons. By evaluating 4 basic image characteristics that were identified in a learning sample, the readers were able to distinguish between images from healthy lungs and pathological lungs. The accuracy of the classification was even higher when the readers were aware of the clinical data (not including radiographic findings). We envision that the combination of breath sound mapping with patient workup is more representative of real life.[28]

The subgroup analysis of patients with pleural effusion showed that the accuracy did not change with the knowledge of the clinical data, and remained high; this may be the result of the disease being highly affected by the distribution of breath sounds. However, the pneumonia subgroup analysis showed that the accuracy improved when the reader knew the patient's workup, probably due to the additional information regarding crackles and acute symptoms such as fever. We studied patients diagnosed as having pneumonia and patients diagnosed as having pleural effusion together, because both pathologies can be identified on chest radiograph and both diseases affect the normal breath sound distribution, usually in a localized manner.

Pleural effusion is a common medical problem and an important source of morbidity,[6,29] but making an accurate diagnosis of pleural effusion is often challenging, even for experts,[29,30] and may cause delay in treatment. Pneumonia is the sixth leading cause of death, and the number one cause of death from infectious diseases in the United States alone.[2,31] Although rapid diagnosis is optimal in the management of pneumonia,[2] physicians frequently disagree on the presence or absence of definitive pneumonia symptoms.[7,32] We propose that the breath sound imaging method we describe here can provide clinically important information to facilitate the diagnosis of common diseases such as pneumonia and pleural effusion. Furthermore, the dynamic nature of the image may broaden our understanding

Fig. 3. Lung sound signals and images from a patient with right-lung pleural effusion. Left panel: Signals of acoustic intensity from the 40 sensors, according to their locations. These signals are of the total recording post-filtering and of an envelope creation. Right panel: The upper image shows breath sound intensity distribution at the start of inspiration. The lower image shows the breath sound distribution at the maximum inspiratory intensity point. A missing signal in the right lower field can be readily identified in both the wave patterns and the images.
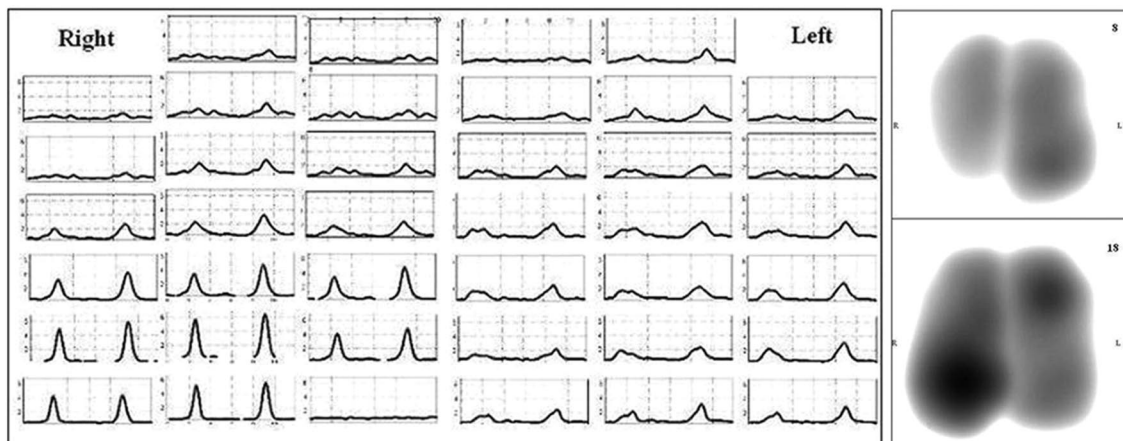

Fig. 4. Lung sound signals and images from a patient with right-lower-lobe pneumonia. Left panel: Signals of acoustic intensity from the 40 sensors, according to their locations. These signals are of the total recording post-filtering and of an envelope creation. Right panel: The upper image shows the breath sound intensity distribution at the start of inspiration. The lower image shows the breath sound intensity distribution at the maximum inspiratory intensity point. The missing part in the right lower field can be readily identified in the upper image, but there are excessive breath sounds in the lower frame (the area of pneumonia), which creates nonsynchronization in the progression of the left and right lungs in the dynamic image.

of lung pathophysiology by providing continuous visualization of acoustic information along the entire breathing cycle as well as detailed information about lung sound timing between the different locations.

Earlier computational adventitious lung sound analysis studies of pneumonia showed the potential of this method for diagnosing lung pathology.[11,28,33] In the present study we investigated the potential utility of displaying breath sound distribution (frequency spectrum 150–250 Hz) in the form of a dynamic image. A previous lung sound imaging study that incorporated a band pass filter of 100–1,000 Hz described one case of a patient with pneumonia and showed a possible correlation between lung consolidation and breath sound distribution.[10] Another study that measured bronchial breathing intensity and incorporated a band pass filter of 300–600 Hz, reported a difference in the ratio of highest inspiratory and highest expiratory flow of the pneumonia lung compared to the contralateral healthy lung.[34] We did not find any documented computational lung sound studies performed on patients with pleural effusion, but decreased breath sounds is a well known phenomenon in pleural effusion.[6] One of the image characteristics we identified in the present study was localized missing parts in the image, which indicate decreased breath

sounds, mainly in the lower lung image. Decreased breath sounds, like other focal lung findings, are known predictors of pneumonia[35] and pleural effusion.[6]

Other abnormalities that have been reported in computerized lung sound studies are regional and sequential differences in breath sounds of patients with emphysema compared to healthy subjects.[21] A lower lung sound intensity and higher lung sound pitch in patients with asthma compared to healthy controls was also reported.[22] Research was performed on breath sound distribution among healthy subjects,[8,10,12,18,26,36] and several groups have reported the reproducibility of breath sounds in that population.[9,23,36] Those studies add credence to the reliability and potential clinical value of computerized lung sound analysis in general and breath sound distribution analysis in particular.

Since we focused our analysis on reporting normal/abnormal findings only, the training for the readers included only basic image features and characteristics, as outlined in the image analysis section above. We believe a higher level of diagnosis will require more extensive training. In our analysis, in a case of disagreement between readers, the finding "abnormal" was chosen; we chose this approach to simulate a situation where the reader is trying not to miss any abnormal finding, which may be related to pathology. This method might have increased the sensitivity and decreased the specificity, but both sensitivity and specificity were high.

Advantages

Auscultation and chest radiograph findings play an important role in the diagnosis of pneumonia and pleural effusion.[2,6] In clinical practice, the physician orders a chest radiograph to confirm suspected lung disease after detecting abnormal lung sounds.[2,6,7] Chest radiographs, however, are imperfect for the diagnosis of pneumonia, pleural effusion, and other lung diseases.[7,37,38] A physician examining a patient with a stethoscope can perceive lung sounds only at isolated locations and at separate time intervals, so evaluation of breath sound distribution relies on the physician's memory and auscultation expertise. In addition, some abnormal lung sounds may be missed even by a chest-auscultation expert in a conventional clinical setting.[3] By using a multisensor device that simultaneously records lung sounds from 40 points over 12 seconds and presents all of the derived information in a single image, the physician can be less dependent on memory. In addition the display mode of a dynamic grayscale image can be more easily interpreted than a multiple graphs view produced by the multiple signals, as shown in Figures 2, 3, and 4. Another advantage of computerized lung sound analysis is the ability to store and later compare the data to subsequent recordings. Importantly, this test can be per-

formed by medical personnel other than the physician, who can evaluate the image later. Finally, this lung sounds examination is noninvasive and harmless, unlike potentially harmful radiologic studies.[16,28]

Limitations

There are several limitations to the present study. We focused on one element of lung sounds (ie, breath sounds), but bronchial breath sounds and adventitious lung sounds are also lung sound components found in respiratory illnesses. A computerized system that detects and displays both breath sound distribution and adventitious lung sounds would probably have greater accuracy than the system we studied. Also, similar to radiographs, the evaluation of the dynamic lung sounds image depends on the reader's ability to discern between qualitative normal and abnormal characteristics. Although this qualitative analysis is essential in understanding the findings in the dynamic image, quantitative results would probably be more objective and improve the accuracy of the findings.

There is also the possibility of not detecting abnormal anterior breath sounds; however, it was reported that acoustic maps measured on the anterior chest wall are less reliable than those measured on the posterior chest wall.[12] Artifacts in the image can be created by direct outer contact of the operator to the sensor or by strong environmental noise. We believe there were some artifacts in our recordings, and better filtration or identification of such artifacts will increase the specificity of the system. Similar to other researchers[11] we studied a convenience sample that was selected after diagnosis was confirmed, rather than consecutive patients. The physicians enrolled only patients who were conventionally diagnosed as having pneumonia, pleural effusion, or healthy lungs. In this study our aim was to differentiate healthy from pathological lungs, so we did not analyze specific image features that can aid in differentiation between pneumonia and pleural effusion. We intend to examine that aspect of the image in future studies.

Conclusions

The good sensitivity and specificity results in the present study show that computerized dynamic breath sound images can be satisfactorily analyzed by trained physicians to distinguish between patients with pneumonia or pleural effusion versus healthy controls. This noninvasive and rapid procedure may aid in the clinical evaluation of patients with lung diseases such as pneumonia and pleural effusion.

REFERENCES

1. Light RW. Clinical practice. Pleural effusion. N Engl J Med 2002; 346(25):1971–1977.
2. Niederman MS, Mandell LA, Anzueto A, Bass JB, Broughton WA, Campbell GD, et al. Guidelines for the management of adults with community-acquired pneumonia. Diagnosis, assessment of severity, antimicrobial therapy, and prevention. Am J Respir Crit Care Med 2001;163(7):1730–1754.
3. Loudon RG. The lung exam. Clin Chest Med 1987;8(2):265–272.
4. Pasterkamp H, Kraman SS, Wodicka GR. Respiratory sounds. Advances beyond the stethoscope. Am J Respir Crit Care Med 1997; 156(3):974–987.
5. Wipf JE, Lipsky BA, Hirschmann JV, Boyko EJ, Takasugi J, Peugeot RL, Davis CL. Diagnosing pneumonia by physical examination: relevant or relic? Arch Intern Med 1999;159(10):1082–1087.
6. Sahn SA. Approach to the patient with a pleural effusion. In: Light RW, Gary Lee YC, editors. Textbook of pleural diseases. London: Arnold; 2003:183–190.
7. Aagaard E, Maselli J, Gonzales R. Physician practice patterns: chest x-ray ordering for the evaluation of acute cough illness in adults. Med Decis Making 2006;26(6):599–605.
8. O'Donnell DM, Kraman SS. Vesicular lung sound amplitude mapping by automated flow-gated phonopneumography. J Appl Physiol 1982;53(3):603–609.
9. Ploysongsang Y, Iyer VK, Ramamoorthy PA. Reproducibility of the vesicular breath sounds in normal subjects. Respiration 1991;58(3–4):158–162.
10. Kompis M, Pasterkamp H, Wodicka GR. Acoustic imaging of the human chest. Chest 2001;120(4):1309–1321.
11. Murphy RL, Vyshedskiy A, Power-Charnitsky VA, Bana DS, Marinelli PM, Wong-Tse A, Paciej R. Automated lung sound analysis in patients with pneumonia. Respir Care 2004;49(12):1490–1497.
12. Charleston-Villalobos S, Cortes-Rubiano S, Gonzalez-Camarena R, Chi-Lem G, Aljama-Corrales T. Respiratory acoustic thoracic imaging (RATHI): assessing deterministic interpolation techniques. Med Biol Eng Comput 2004;42(5):618–626.
13. Sovijärvi AR, Vanderschoot J, Earis JE. Standardization of computerized respiratory sound analysis. Eur Respir Rev 2000;10(77):585.
14. Gavriely N, Nissan M, Cugell DW, Rubin AH. Respiratory health screening using pulmonary function tests and lung sound analysis. Eur Respir J 1994;7(1):35–42.
15. Bergstresser T, Ofengeim D, Vyshedskiy A, Shane J, Murphy R. Sound transmission in the lung as a function of lung volume. J Appl Physiol 2002;93(2):667–674.
16. Mauri D, Kamposioras K, Proiskos A, Xilomenos A, Peponi C, Dambrosio M et al. Old habits die hard: chest radiography for screening purposes in primary care. Am J Manag Care 2006;12(11):650–656.
17. Sovijärvi AR, Dalmasso F, Vanderschoot J, Malmberg LP, Righini G, Stoneman SA. Definition of terms for applications of respiratory sounds. Eur Respir Rev 2000;10(77):597–610.
18. Dosani R, Kraman SS. Lung sound intensity variability in normal men. A contour phonopneumographic study. Chest 1983;83(4):628–631.
19. Ploysongsang Y, Martin RR, Ross WR, Loudon RG, Macklem P. Breath sounds and regional ventilation. Am Rev Respir Dis 1977; 116(2):187–199.
20. Lynch T, Platt R, Gouin S, Larson C, Patenaude Y. Can we predict which children with clinically suspected pneumonia will have the presence of focal infiltrates on chest radiographs? Pediatrics 2004; 113(3):e186–e189.
21. Ploysongsang Y, Pare JA, Macklem PT. Lung sounds in patients with emphysema. Am Rev Respir Dis 1981;124(1):45–49.
22. Schreur HJ, Vanderschoot J, Zwinderman AH, Dijkman JH, Sterk PJ. Abnormal lung sounds in patients with asthma during episodes with normal lung function. Chest 1994;106(1):91–99.
23. Sovijärvi AR, Malmberg LP, Paajanen E, Piirila P, Kallio K, Katila T. Averaged and time-gated spectral analysis of respiratory sounds. Repeatability of spectral parameters in healthy men and in patients with fibrosing alveolitis. Chest 1996;109(5):1283–1290.
24. Fine MJ, Auble TE, Yealy DM, Hanusa BH, Weissfeld LA, Singer DE, et al. A prediction rule to identify low-risk patients with community-acquired pneumonia. N Engl J Med 1997;336(4):243–250.
25. Davies CW, Gleeson FV, Davies RJ. BTS guidelines for the management of pleural infection. Thorax 2003;58(Suppl 2):ii18–ii28.
26. Ploysongsang Y, Macklem PT, Ross WR. Distribution of regional ventilation measured by breath sounds. Am Rev Respir Dis 1978; 117(4):657–664.
27. Landis J, Koch GG. The measurement of observer agreement for categorical data. Biometrics 1977;33(1):159–174.
28. Bettencourt PE, Del Bono EA, Spiegelman D, Hertzmark E, Murphy RL. Clinical utility of chest auscultation in common pulmonary diseases. Am J Respir Crit Care Med 1994;150(5 Pt 1):1291–1297.
29. Maskell NA, Butland RJA. Pleural Diseases Group, Standards of Care Committee, British Thoracic Society. BTS guidelines for the investigation of a unilateral pleural effusion in adults. Thorax 2003; 58(Suppl 2):ii8–ii17.
30. Diacon AH, Brutsche MH, Soler M. Accuracy of pleural puncture sites: a prospective comparison of clinical examination with ultrasound. Chest 2003;123(2):436–441.
31. Garibaldi RA. Epidemiology of community-acquired respiratory tract infections in adults: incidence, etiology, and impact. Am J Med 1985;78(6B):32–37.
32. Metlay JP, Kapoor WN, Fine MJ. Does this patient have community-acquired pneumonia? Diagnosing pneumonia by history and physical examination. JAMA 1997;278(17):1440–1445.
33. Vyshedskiy A, Bezares F, Paciej R, Ebril M, Shane J, Murphy R. Transmission of crackles in patients with interstitial pulmonary fibrosis, congestive heart failure, and pneumonia. Chest 2005;128(3): 1468–1474.
34. Gross V, Fachinger P, Penzel T, Koehler U, von Wichert P, Vogelmeier C. Detection of bronchial breathing caused by pneumonia. Biomed Tech (Berl) 2002;47(6):146–150.
35. Diehr P, Wood RW, Bushyhead J, Krueger L, Wolcott B, Tompkins RK. Prediction of pneumonia in outpatients with acute cough–a statistical approach. J Chronic Dis 1984;37(3):215–225.
36. Mahagnah M, Gavriely N. Repeatability of measurements of normal lung sounds. Am J Respir Crit Care Med 1994;149(2 Pt 1):477–481.
37. Bartter T, Santarelli R, Akers SM, Pratter MR. The evaluation of pleural effusion. Chest 1994;106(4):1209–1214.
38. Wilkins TR, Wilkins RL. Clinical and radiographic evidence of pneumonia. Radiol Technol 2005;77(2):106–110.