Accuracy of gray-scale coding in lung sound mapping

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\textbf{A B S T R A C T}

Stethoscope evaluation of the lungs is widely accepted and practiced; however, there are some widely recognized, major limitations with its use. A safe device that helped solve these limitations by translating sound into objective, quantifiable images would have clinical utility. Translating lung sounds into quantifiable images in which regional differences or asymmetry in intensities of breath sounds are presented as gradients in gray-scale is not a trivial process. Healthy lungs and lung pathology are characterized by different patterns of regional breath sound distribution and, therefore, the accuracy of mapping gray-scale images must be ensured in a controlled systematic fashion prior to introduction of such a technique. Vibration response imaging (VRI) maps lung sounds from 40 sensors to a two-dimensional gray-scale image. To assess mapping accuracy, a simulated lung sound map with uniform signals was compared to modified maps where sound signals were reduced (1–3 db) at one sensor. Also, 8 readers evaluated the gray-scale images. The computer algorithm accurately displayed gray-scale coding changes in correct locations in 97% of images. There was 95 ± 4% accuracy rate by readers to correctly identify gray-scale changes. In addition, quantitative data at different stages of signal processing were investigated in a LSM of a subject with asthma. Signal processing was 97% accurate overall in that the gray-scale values from which the image was derived corresponded with intensity values from recorded signals. These results suggest VRI accurately maps acoustic signals to a gray-scale image and that trained readers can detect small changes.

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1. Background

Accurate identification of respiratory signs is an important component in the clinical diagnosis of respiratory pathology. The reliability of eliciting physical signs in examination of the chest is relatively poor with 28% of diagnoses being incorrect [1]. Auscultation is a subjective process that is dependant on the auditory acuity and clinical experience of the user and, thus, a quantitative method to obtain reliable information and documentation of lung sounds has been the focus of many investigators.

In the past two decades, computer-based technology has evolved to evaluate the acoustic properties of respiratory sounds and to provide objective measurements that may circumvent the shortcomings of clinical auscultation. A number of studies have investigated the reliability of acoustic analysis and practical application of this method in clinical diagnosis [2–11]. A multi-national effort was made to establish guidelines on methods of recording and analysis of breath sounds in an attempt to standardize terminology [12].

The display of computerized-based lung sound data varies from graphs of amplitude versus frequency [13], to graphic maps of amplitude contour [14,15], and to gray-scale sound intensity maps [8]. Creating a lung sound map reflecting spatial distribution of sound intensity from a set of signals recorded on a reduced set of spatial coordinates presents the challenge of how to increase spatial resolution without distorting the recorded information. A thorough discussion of approaching this challenge with methods of interpolation has been previously presented [16]. We recently described a new computer-based modality for recording, quantifying, and mapping lung sounds to a two-dimensional gray-scale dynamic and static image [17]. We have termed this modality “vibration response imaging” (VRI). Examples of common characteristics in the normal image, as well as images from patients with various respiratory pathologies have been published [17–24].
gray-scale coded values that represent a regional distribution pattern for each of the 71 frames in 12 s of recording. Depending on the clinical situation, regional differences or asymmetry in intensities of breath sounds or evidence of adventitious sounds in gray-scale images may prompt, similar to stethoscope use, additional physical examination maneuvers, further diagnostic evaluations (e.g., a chest radiograph), and sometimes treatment. Therefore, the accuracy of mapping acoustic signals to gray-scale images must be ensured in a controlled environment prior to clinical use of such a technique.

The algorithm was designed to take into account the heterogeneity of lung sound distribution and, therefore, if the algorithm is sufficiently robust, then it should demonstrate that even a small decrement of change in adjacent locations can be detected and translated accurately into a quantifiable gray-scale image. Even healthy lungs exhibit some degree of inhomogeneity in lung sound distribution [2,15] and gray-scale images [19,23]. Moreover, this inhomogeneity is emphasized in lung pathology and is reflected in the gray-scale image [18,22].

Given that, the present study was designed to establish the accuracy of the computer algorithm underlying the images created by this system by simulating an environment in which homogeneity of lung sound distribution was absolute and any change in gray-scale distribution was controlled. The first goal was to determine whether small gradients in lung sound intensity were accurately reflected in the displayed image. The second goal was to determine the precision of trained readers to detect these small gradients in gray-scale sound intensity in the images under the best of conditions when the images were purposefully homogeneous. The third goal was to map acoustic signals from a patient with clinical asthma to validate that the intensities of recorded acoustic signals were processed correctly to values for a gray-scale visual image (i.e., louder signals would appear as darker zones in the image based on the gray-scale pixel count values).

2. Methods

2.1. Description of device

The VR1xp™ technology (Deep Breeze™, Or-Akiva, Israel) incorporates 40 active, piezoelectric contact sensors (Meditron ASA, Oslo, Norway) that capture and record lung sounds during the respiration process. The sensors are mounted in two matrices, set in seven rows and three columns (Fig. 3); the two peripheral sensors in the upper row are inactive sensors. The matrices are attached to the posterior chest by a PC-controlled, low vacuum that maintains a constant and simultaneous mechanical load on the sensors. The electrical signals are transmitted through wires from the sensors to the hardware board. The analog signals are then processed by a 64 multi-channels hardware board by amplifying, sampling and A/D conversion (16-bit acquisition level and a sampling rate of 19.2 kHz). The digital data is transmitted to the PC platform where it is processed by the device algorithm and then displayed as a dynamic image.

2.2. Device algorithm

The VR1xp™ technology’s algorithm combines the output signals to assemble a gray-scale dynamic image (Fig. 1), or a sequence of lung sound maps (LSM). The gray-scale pattern represents the data signals at each sensor position. N sensors (40 active sensors) are configured for attachment to an essentially planar region, R, on the subject’s back [17]. Positions in the region R are designated by two-dimensional position vectors, \( x = (x_1, x_2) \). The i sensor (i = 1 to N) is fixed at a position \( x_i \) in the region R and generates a signal,
denoted herein by $p(x_i, t)$ that is indicative of pressure waves in the body arriving at $x_i$. A sound envelope (EVP) is obtained from the signal at each of the $N$ sensors, as follows: the digitized sound signal is band-pass filtered between 150 and 250 Hz in order to select only the desirable frequency range of breath sounds [11] and to reduce other interfering sounds, e.g. heart, muscles, environmental noise, etc. [8]; median filtering is applied to suppress impulse noise, and then truncation of samples above a pre-defined threshold is performed. Additionally, Singular Value Decomposition is used to detect and extract small signals from noisy data. Then the average vibration energy over a short time interval (frame with duration 0.17 s) is obtained for signals from each of the sensors. Thus, the energy is calculated at each position of the sensors in 71 points along a time scale. For all $N$ sensors, the lower energy threshold is defined as 4% of the maximum value calculated from all $N \times 71$ EVP values.

The energy distribution is displayed in the LSM as 256 degrees of gray-scale coded values from white to black colors. The size of the map is 750 x 750 pixels. Each of the 562,500 pixels is defined within the gray-scale scheme and combined to create the LSM for each frame of the dynamic image. A column of pixel grids, corresponding with location of the vertebral column, is automatically defined as white. The sensors signals are mapped in 70 pixel intervals in each direction with gray-scale coding from the darkest shade (high data values), in which lung sound is greatest, to white (low data values). The ratio between gray-scale values of different positions within the LSM is dependent on the intensity and location of signals. Each of the sensors has a defined position that corresponds with a specific pixel grid within the LSM (Fig. 4). High data areas, where breath sound intensity are greatest, are depicted as dark colors (black) within the 256 hues and low data areas are shown in light colors (light gray); the minimum data area is depicted as white. Each subject’s recording has different high and low value areas within each respiratory cycle, according to the breath sound intensity. Generally, a breath sound has higher intensity in comparison to any background noise; therefore, these sounds will be the dominating input in the gray-scale distribution. Moreover, the 4% energy threshold eliminates values that generally correspond to noise. A graph of breath sound intensity versus time on a linear time scale is presented under the image (Fig. 1).

### 2.3. Study design of LSM gray-scale accuracy

The following bench tests were performed under controlled conditions. Lung sounds recorded for 12 s during three respiratory cycles of one healthy volunteer were used to produce a basic signal from the central sensor of the left lung (position 3-2). The sensors have a defined position (denoted by the numbers in the horizontal and vertical column numbers, respectively) that corresponds with a specific pixel grid within the LSM (Fig. 4). The signal was duplicated 40 times, using MATLAB version 7.1 (The MathWorks, Inc., Natick, Massachusetts) in order to simulate a uniform LSM, consisting of 71 frames, from the 40 identical lung sound signals (Fig. 5). Modified LSMs were created by decreasing the sound of the signal by 1, 2, or 3 decibels (dB) in a single sensor (Fig. 6). These decrements are equal to a decrease of 21%, 37%, and 50%, respectively. They were selected because they are the minimum changes in sound that the human ear can detect [25]. Thus, three modified LSM intensity subgroups were formed. This process was applied to all 40 sensors; thereby 120 modified LSMs and one uniform LSM were produced for evaluation.

In order to determine if decreases in the intensity of sound signals were reflected in the LSM, modified LSMs were compared with the uniform LSMs. For each LSM, each sensor was assigned a value that was equal to the sum of gray-level values in its corresponding area. Gray-scale value decrements in the pixel grids of each sensor were calculated by multiplying the pixel area of the single sensor grid (70 x 70 pixels) by the gray-scale value (from 0 to 255). The maximum value of 1,249,500 (70 x 70 x 255) was computed.
in order to normalize the values to a range of 0% (no change) to 100% (maximum change) in order to calculate the average gray-level decrement. The level of the change and the location of change were determined for each frame of the LSM in which the change was consistent in the modified sensor. Success was defined as a change of at least one gray-level in the pixels in areas of the modified sensor in all analyzed frames for all the modified LSMS.

The maximum change that occurred in the modified LSM should be observed in the pixel areas corresponding to the sensor that was modified. If this condition exists in at least 96% of the analyzed frames within all 120 modified LSMSs then the intensity parameter is validated. This success criterion is due to the inherent boundaries of the dynamic range set forth by the algorithm in order to normalize the gray-scale image. Energy values below the 4% threshold (see Section 2.2) are automatically defined as white and maximum energy values are automatically defined as black in the gray-scale scheme and so changes in intensity in areas of the modified sensor, where the part of it is below the 4% threshold or has maximum value, would not be observed. The LSM success of the algorithm was statistically compared between the three modified LSMs intensity subgroups by t-test for paired data, Fisher’s exact test and confidence interval (CI).

### 2.4. Study design for rater evaluation of LSMS

The second phase of the study evaluated the ability of trained, blinded raters to visually detect small gradients in lung sound intensity, represented as gray-scale changes in the LSM. Simulated LSMSs were prepared in the same manner as the first phase of the study. A total of 180 LSMSs consisting of both uniform (n = 40) and modified (n = 140) LSMSs, were produced for evaluation and randomly presented to the raters. Within the group of 140 LSMSs, 20 of the modified LSMSs were duplicated for estimating the intra-rater reliability effect. All the evaluations were performed on Eizo screens (FlexScan L557 size 17”) with Windows Media Player Classic software.

Eight blinded raters (2 pulmonologists, 3 primary care physicians, and 3 clinical data analysts) were trained to identify intensity changes in the LSM. During the evaluation, the raters examined the dynamic image and then each of the 71 consecutive static frames. The raters then reported if the LSM was modified or uniform. If the LSM was modified, the raters reported the location of the modification (within the upper, middle or lower rows of the right or left lung). All observations were recorded on an evaluation form.

Intra-rater reliability was defined independently for each of the eight raters as the percentage of LSMSs that were assessed identically. This analysis set was based on 30 LSMSs (20 modified, 10 homogeneous) from the 180 LSMSs. Intra-rater reliability was a prerequisite for including the assessments of the raters. Evaluations of raters with less than 80% (allowed maximum: 6 mismatches of 30 LSMSs) of intra-rater reliability were not included in the accuracy analysis.

Accuracy analysis was performed on 160 LSMSs (40 homogeneous LSMSs and 120 modified LSMSs; the 20 modified LSMSs from the intra-rater reliability analysis were not included). Success was defined as a rater’s ability to correctly identify the LSM as homogenous or modified, and if modified, then to correctly identify the location of the change. The accuracy rate of each rater’s assessments is the number of successful evaluations (n_{success}) divided by the number of evaluated LSMSs (160). The overall accuracy rate for all eligible raters (maximum eight raters) was calculated as follows:

\[
\text{Accuracy Rate} = \frac{\sum_{i} n_{success}}{160 \times i}, \quad i = \text{rater (1, \ldots, 8)}
\]
Accuracy parameters were calculated for each rater separately and averaged for all raters (with high intra-rater reliability). Common errors were also investigated in order to determine which parameters had a higher probability for error. The errors were evaluated for the following parameters: intensity mode (decrease or no modification), intensity level (1 dB, 2 dB, or 3 dB), and location (central, outer peripheral, inner peripheral, or corner sensor).

2.5. LSM of subject with lung pathology

In addition to investigating the accuracy of the gray-scale image under controlled conditions (simulated LSMs), another test was performed to validate that the intensities of recorded acoustic signals from a subject with asthma (actual clinical data) were processed correctly to a gray-scale visual image (i.e. louder signals appear as darker zones in the image). Values for the sound envelopes (EVP values) were obtained from the signal at each of the 40 sensors. The gradients (slope) between the EVP value of the analyzed sensor and the EVP values of all its adjacent sensors were tested for each sensor. The signs (positive, negative) of these gradients, before and after algorithm processing, were compared under the assumption that the sign should not be changed.

3. Results

3.1. LSM gray-scale accuracy

The sound signal, which was captured by one central sensor during 12 s of recording, had a noise range of 26.7 dB. At the modified sensor, the sound decrements of 1 dB, 2 dB, and 3 dB, represented a change of 21%, 37% and 50%, respectively, as compared to the non-modified sensor. After transforming the signal to an LSM, a pixel-by-pixel analysis was performed, in order to assess the performance of the gray-scale algorithm. The uniform LSM showed no gray-level change and had a uniform gray-scale value for the 562,500 pixels. In the modified LSMs, a change of one gray-level or more was detected in the modified sensor in all the analyzed frames.

A maximum gray-level change occurred in a location that corresponded with the location of the intensity modification in all modified 120 LSMs (in at least 96% of the analyzed frames). The change value ranged from 5% (13 gray-levels) to 21% (54 gray-levels). In 78% (94 of 120) of the LSMs, the maximum change was observed at the corresponding modified sensor in all analyzed frames. In 22% (26 of 120) of the LSMs, the maximum change was observed in the modified sensor in 97% of the analyzed frames, and in 3% the maximum change was observed in the sensor adjacent to the modified sensor. This occurred in sensors that are located at the corners (at 10 corner sensors) in frames where a part of the area corresponding to these sensors had a white color because of the dynamic range definition.

As the sound reduction level was modified according to a scale of 0–1 dB (and 2 dB and 3 dB), the sound decrease rate and percentage of gray-scale absolute change increased (Table 1). A greater decrease in signal intensity resulted in a higher percentage reduction in gray-scale. The average values for percentage change in the LSMs were 7.1 ± 1.4%, 12.9 ± 2.2% and 16.4 ± 3.0% for 1 dB, 2 dB and 3 dB sound modifications, respectively, which are 18.3 ± 3.1, 32.7 ± 5.8, 42.0 ± 7.6 in gray-scale units. The differences in observed changes between any two of the three intensity levels (i.e. 1 dB versus 2 dB) were significant (p < 0.05, t-test for paired data; see Table 1).

3.1.1. LSM of subject with lung pathology

There were 146 optional comparisons between each of the 40 sensors and adjacent sensors’ gradients. The algorithm was 97% (142/146) accurate in processing and translating recorded signals to gray-scale values. Due to the built-in constraints set forth by the dynamic range, values under the lower threshold are set to the actual lower threshold value and would appear white. The regional breath sound distribution in the gray-scale image of the asthmatic patient showed a significantly different mapping pattern (Fig. 7) than a typical pattern in a healthy individual (Fig. 1).

3.2. Rater evaluation of LSMs

The second phase of the study investigated the hypothesis that trained blinded raters had the ability to detect gradients in lung sound intensity, as represented in gray-scale changes in the LSM. A prerequisite for inclusion in the rater analysis was high intra-rater reliability. The overall intra-rater reliability average for the

<table>
<thead>
<tr>
<th>Sound reduction level (dB)</th>
<th>Intensity decrease in gray-scale units</th>
<th>Intensity decrease in gray-scale (in %)</th>
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<tbody>
<tr>
<td></td>
<td>(lower, upper 95% confidence intervals)</td>
<td>(lower, upper 95% confidence intervals)</td>
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<td>0 dB decrease</td>
<td>(0, 0)</td>
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<tr>
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<td>(17, 19)</td>
<td>(75, 83)</td>
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<tr>
<td>2 dB decrease</td>
<td>(31, 35)</td>
<td>(12%, 149)</td>
</tr>
<tr>
<td>3 dB decrease</td>
<td>(40, 44)</td>
<td>(15%, 177)</td>
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eight raters was 94 ± 6% (range 83–100%). Seven of the eight raters had an intra-rater reliability of 90–100%. All the raters had high intra-rater reliability and their evaluations were included in the accuracy analysis.

Results were based on evaluation of a total of 1280 LSMs (8 blinded evaluations for 160 LSMs). There was a 95 ± 4% (1218/1280) overall accuracy rate for the eight raters to correctly identify changes in gray-scale and the location that corresponded with an intensity decrease in one sensor. Error rate per rater ranged from 0% to a maximum of 12.5% (20/160).

Three types of errors were identified: (a) modified LSMs erroneously reported as uniform (3.4%), (b) uniform LSMs that were erroneously reported as modified (1.3%), and (c) inaccurate detection of signal decrease location (0.2%). The error types, (a) and (b), represent the sensitivity (96%) and specificity (95%), respectively, of LSM assessment. The lowest sensitivity (89%) was observed for sound intensity decreases of 1 dB, while greater decreases in sound intensity (2 dB and 3 dB) were more consistently discerned by the raters (sensitivity of 99%) (Table 2). The lowest intensity level (1 dB) resulted in the highest error rate (p < 0.05); in contrast, there were no significant differences between 2 dB and 3 dB (p > 0.05, Fisher’s exact test).

The eight raters had 62 false assessments for the 1280 LSMs that were evaluated. These false assessments occurred in 42 images, representing 42 different combinations of locations and intensity levels. Thirteen images were wrongly assessed by more than one reviewer (Table 3).

The highest rate of evaluation errors occurred for 1 dB decreases in a corner sensor (n = 16) and for 1 dB decreases in a central sensor (n = 14). These errors accounted for 48% (30/62) of the total evaluation errors in the study. The corner and central sensors had a significantly higher rate of error than the peripheral sensors (p < 0.05); there were no significant differences between central and corner sensors (p > 0.05, Fisher’s exact test).

The accuracy of identifying the location of an LSM intensity change was 99.7% (957/960; 960 = 120 modified LSMs × 8 raters). One of the eight raters reported the wrong location of an intensity change in three LSMs. Two location errors were the result of an intensity decrease in one sensor. Error rate per rater ranged from 0% to a maximum of 12.5% (20/160).

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improves clarity of gray-scale gradients, as there were only two errors in identifying gray-scale changes in the outer periphery.

While excellent results were demonstrated by the raters in this study, it is acknowledged that the LSMs were prepared under controlled and optimal conditions. The original signal was derived from an actual recording, in order to simulate conditions that would exist in a clinical setting; however, the remaining signals were duplicated and modified by the software and likely had an optimal signal-to-noise ratio. A slightly lower accuracy rate would be expected if raters identified changes that would occur in more than one sensor from a recording in a clinical setting. Nonetheless, the current results do show that raters are able to visually perceive even 1 db differences in the LSM under optimal conditions.

Due to the inherent limitations of auscultation, more objective methods have been sought to evaluate respiratory sounds. Methods based on computer analysis of acoustic pulmonary signals provide objective measurements based on reproducible data that are analyzed in terms of quantitative parameters. Results of computerized lung sound data are usually presented in various dynamic forms such as amplitude versus time, intensity versus frequency or amplitude versus frequency [2,5,15]. Results can also be displayed as a continuous varying signal of power spectra versus time in a three-dimensional coordinate system or as a sonogram representing the plane frequency versus time [8,9]. VRI technology presents breath sounds as a two-dimensional gray-scale dynamic image derived from EVP values across a spatial matrix covering the lung area and across a time period. Thus the VRI technology allows the simultaneous observation of breath sounds captured by 40 sensors in a single dynamic image, as opposed to 40 separate graphs. A visual representation of the lung sound data provided by the VRI has the advantage of displaying the information in a dynamic format as well, thereby, enhancing the value of this data and enabling the observer to also detect timing differences between the different parts of the lung. Currently, we are conducting a study to examine time delay perception by blinded raters. Time delay perception will most likely assist reviewers in detecting respiratory dynamic disturbances and provide new insights into important issues in lung mechanics, such as regional interdependence, airway-parenchyma interactions and parallel inhomogeneity [26].

5. Conclusions

We have demonstrated that the VRI computer algorithm for gray-scale coding of acoustic signals is robust and that even small gradients in the gray-scale image can be evaluated by a trained rater with excellent accuracy. Reviewers were able to distinguish the spatial lung sound characteristic of intensity differences in a 70 × 70 pixel grid, corresponding to one sensor, in all locations of the image. Furthermore, the clinical example of lung sounds mapped in a subject with lung pathology provides support that the algorithm can accurately process the intensities of recorded acoustic signals to a gray-scale visual image not just from simulated data, but also from actual clinical data. Presently, the VRI™ technology is under research for potential clinical applications in order to improve our understanding of the LSM characteristics that are associated with various respiratory diseases.

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References


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