Detection of Respiratory Crackle Sounds via an Android Smartphone-based System

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***Abstract*—Pulmonary auscultation with traditional stethoscope, although useful, has limitations for detecting discontinuous adventitious respiratory sounds (crackles) that commonly occur in respiratory diseases. In this work, we present the development of a mobile health system for the automated detection of crackle sounds, comprised by an acoustical sensor, a smartphone device, and a mobile application (app) implemented in Android. The app allows the physician to record, store, reproduce, and analyze respiratory sounds directly on the smartphone. The algorithm for crackle detection was based on a time-varying autoregressive modeling. Performance of the automated detector was analyzed using synthetic fine and coarse crackle sounds randomly added to the basal respiratory sounds acquired from healthy subjects with different signal to noise ratios. Accuracy and sensitivity were found to range from 90.7% to 94.0% and from 91.2% to 94.2%, respectively. Application of the proposed mobile system to real acquired data from a patient with pulmonary fibrosis is also exemplified.**

I. Introduction

Early diagnosis of respiratory problems is important to prevent chronic respiratory diseases and to take prompt actions. For example, hypersensitive pneumonia that could lead to pulmonary fibrosis and death could be reversed if diagnosed in its early stages. The first approach used in the noninvasive diagnosis of respiratory diseases involves the clinical history together with auscultation with the stethoscope. Presence of crackle sounds, considered as discontinuous adventitious lung sounds (LS), is a usual finding during auscultation. However, their detection is highly dependent on the ability and expertise of the physician. In addition, detection of crackles during the auscultation is challenging due to their temporal and spectral characteristics, i.e., transient, short lasting (<20 ms), broad frequency content (between 100 up to more than 1000 Hz) that evolves with time [1], waveform temporal overlapping and relative magnitude compared to base LS. Similarly, visual detection of crackles via the proposed time-expanded waveform analysis (TEWA) becomes cumbersome [2].

Computerized methods have been proposed to overcome limitations of the audiovisual detection of crackles, *e.g.*, automated detection based on signal processing techniques like time-frequency analysis [3] or time-varying autoregressive modeling [4]. Unfortunately, the use of computerized respiratory sound analysis (CORSA) systems is mainly limited to research and specialized healthcare centers which cannot be easily translated outside those settings because of their limited mobility or high costs.

Mobile health (mHealth), understood as the use of mobile and wireless technologies to support the achievement of health objectives, has the potential to transform health delivery worldwide. Mobile devices like smartphones have characteristics that are transferred when used for health purposes, e.g., being ubiquitous and connected, allowing healthcare professionals to use them for monitoring of health status in the natural environments of the general population [5]. It is well known that usage of smartphone apps for healthcare purposes is on the rise. The trend is expected to sustain considering the need for developing systems that alleviates the overload in healthcare systems and reduce healthcare costs. Perhaps the most widely known use of smartphone-based monitoring is the estimation of heart rate via the smartphone video camera. Alongside, our research group and others have made efforts to develop mobile CORSA (mCORSA) systems [6], [7].

In this work, we present results towards the development of a CORSA system for the task of automated detection of crackle sounds directly on a smartphone running Android OS given its dominance in the global market. The proposed system was designed to take advantage of the standard audio input, present in most of the currently available smartphone devices, so that an acoustical sensor specifically developed for LS analysis can be straight forwardly attached to it [4]. Different scenarios were simulated to test the performance of the automated detector at different signal-to-noise ratios (SNR) and different types of crackles, to say, fine (higher frequencies) and coarse (lower frequencies) crackles. In

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addition, we present the application of the proposed system to real acquired data from a patient with respiratory disease.

II. Methodology

A. Hardware components of the system

The proposed mHealth system consists of: 1) an acoustic sensor, and 2) a smartphone device, as shown in Fig. 1.a. The acoustic sensor for respiratory sounds consists of an electret subminiature microphone (BT-2159000, Knowles Electronics, Itasca, IL, USA) encapsulated in a plastic bell designed for adequate acquisition of respiratory sounds as described in [4], and was connected to the 3.5 mm audio input of the smartphone. Two smartphone models have been used in the development of the system: 1) Galaxy S4 manufactured by Samsung and running Android v5.0.1, and 2) Moto G Turbo Edition manufactured by Motorola and running Android v6.0. Both devices were selected because they provide reliable digitalization requirements as recommended [8].

B. Mobile application (app)

The mobile application was developed with the official IDE Android Studio (Google Inc., Mountain View, CA, USA) on a personal computer running Windows 10 OS with Intel processor (i7-6500U) and 16 GB of RAM. In addition to testing the app development using emulated devices in Android Studio, the app has been tested on both physical smartphones, i.e., Galaxy S4 and Moto G devices.

B.1. Graphical User Interface (GUI)

A splash-screen welcomes the user, as shown in Fig. 1.a, and then an app activity allows him/her to, either: 1) adding a new patient to the list, or 2) selecting an existing patient from previously registered ones. If adding a new patient option is chosen, an app activity allows introducing basic information of the patient and validating it. If selecting an existing patient option is chosen, the app displays the information of the patient and a list with his/her existing sound recordings so that one can be selected to analyze it. In both cases, the user has the option to acquire a new respiratory sound recording.

B.2. Acquisition and pre-processing of respiratory sounds

Respiratory sounds are acquired at a sampling rate (fs) of 10 kHz using 16 bits-per-sample. Inside the app, acquired sounds are digital filtered using a 500th order finite impulse response (FIR) bandpass filter between 100 and 1000 Hz. Recorded sounds can be stored in the mobile device in both audio and text formats for their processing directly in the smartphone or for exporting them to another one.

B.3. Respiratory maneuver and auscultation focus points

An app activity allows to select an auscultation focus point by touching a graphical array of locations proposed to cover the left (L) and right (R) hemithorax by means of a 3x2 matrix (rows: apical (A), medial (M), and basal (B) and columns: interior (i) and exterior (e)). An additional auscultation point on the trachea was included for future applications. Once the auscultation point is selected, an app activity allows the user to control the sound acquisition, as shown in Fig. 1.b. While recording, the app fills the area under the maneuver curve to aware the subject when to inspire (I) and expire (E), according to fixed respiratory frequency. The respiratory maneuver consists of 2 s of initial apnea, 4 breath cycles with a duration of 4 s each (I:E ratio of 2:3), and 2 s of final apnea. The sound recording can be stored, reproduced or discarded by the physician.

C. Algorithm for automated detection of crackles

The algorithm implemented in the smartphone app for detection of crackles was based on locating abrupt changes in the coefficients of a time-varying autoregressive (TVAR) model generated by the transient characteristics of crackles with respect to the basal LS [4]. The TVAR model of a discrete stochastic signal is given by

$$s[n] = -\sum_{k=1}^{M} a_k[n]s[n-k] + v[n] \qquad (1)$$

where M is the model order, the set of $\{a_k[n]\}_{k=1,\cdots,M}$ are the TVAR coefficients at time n, and $s[n-k]$ are past samples of $s[n]$ and $v[n]$ is a white noise process [9]. The developed app estimates the TVAR coefficients at each time instant using the recursive least squares algorithm (RLS) which employs a forgetting factor, λ, to control the influence of prior information on which the cost function in equation (2)

$$\xi[n] = \sum_{i=1}^{n} \lambda^{n-i}|e[i]|^2 \qquad (2)$$

is minimized, where $e[n]$ is the error of the adaptive filter. Based on Akaike´s criterion and in our previous study, the developed app employs a 4th order TVAR model (M=4) and a forgetting factor close to the unity, λ=0.97, as found to be adequate for crackle detection [4]. Once the TVAR coefficients are computed, their abrupt changes are detected via the local maxima of the sum of the absolute value of the TVAR derivatives by employing a threshold equal to thr=0.031 and a moving window of 4 ms duration. The threshold parameter was set using a grid search approach, as shown in Fig. 2, so that the maximum accuracy of the

a) b)

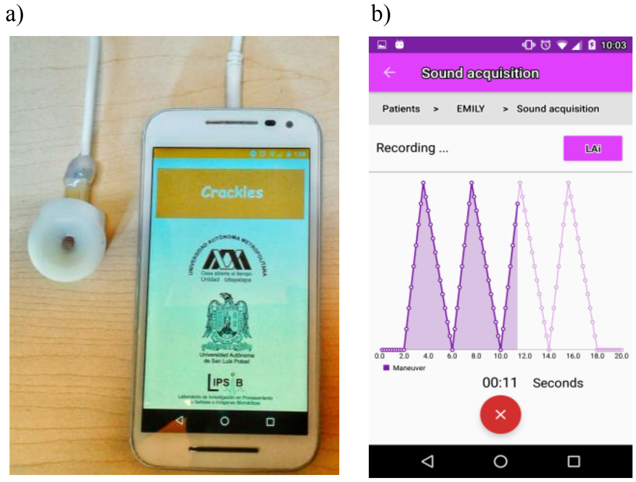

Figure 1. Mobile system for automated detection of respiratory crackles. a) Welcome screen and acoustic sensor. b) App activity for respiratory sound acquisition displaying a breathing maneuver.

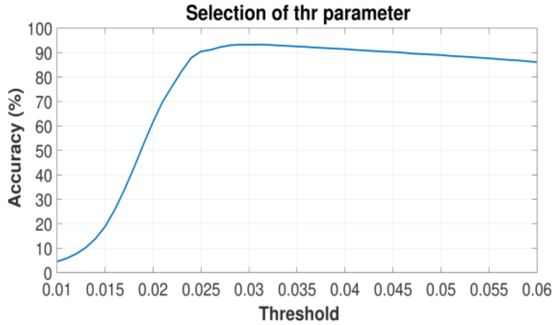

Figure 2. Accuracies of the automatic crackle detector versus threshold values used to detect transients in TVAR coefficients.

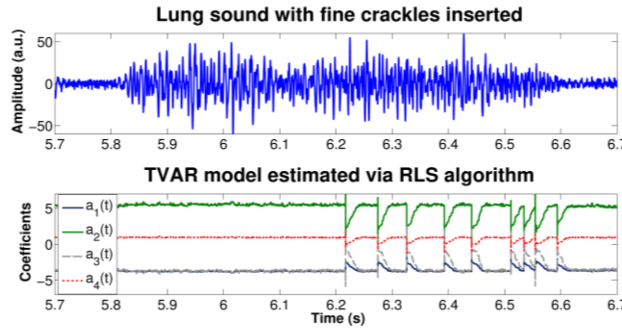

Figure 3. Time evolution of TVAR coefficients (bottom) as computed by the smartphone app for a lung sound with inserted crackles at the end of inspiration.

detector was obtained for all simulated scenarios.

D. Acquisition of LS from healthy subjects and patients

Respiratory recordings from ten (N=10) healthy, non-smoking subjects were acquired at the National Institute of Respiratory Diseases in Mexico. Recordings were acquired with the system at *fs*=10 kHz while the subjects performed the respiratory maneuver described before. Recording and labeling, i.e., manual location of crackles by pneumologists, of respiratory sounds acquired from patients with respiratory diseases, e.g., pulmonary fibrosis, is currently ongoing to evaluate the app performance with real data.

E. Simulated scenarios of LS with crackles

To test the performance of the detector, synthetic crackles were generated and randomly inserted in the acquired healthy LS in three different scenarios to reflect conditions found in clinical practice: 1) 10 fine crackles at beginning of each inspiration, 2) 10 fine crackles at end of each inspiration, and 3) 10 fine crackles at each inspiration and 10 coarse crackles at each expiration. For each scenario, crackles were added to base LS with three different gain factors equal to 1.5, 2.5 and 3.5 times the variance of the LS in the corresponding insertion window to simulate different SNR. Synthetic crackles were generated as

$$x(t) = sin^2(\pi\sqrt{t})\sin\left(4\pi t^{\frac{\log(0.25)}{\log(T_0)}}\right), \qquad 0 \le t \le 1 \tag{3}$$

where the T_0 refers to the initial deflection width (IDW) and the two cycles duration (2CD) corresponds to the crackle duration, which were set for synthetic fine and coarse crackles to 0.5 and 5 ms, and 1.2 and 9 ms, respectively.

E. Performance of the crackle detector

The accuracy (Acc) and sensitivity (Sen) indices given by

$$Acc = \frac{TP}{TP+FN+FP} \quad , \quad Sen = \frac{TP}{TP+FN} \tag{4}$$

were employed to quantify the performance of the crackle detector in simulated scenarios, where TP are the true positives (correct detection), FN are the false negatives (missing detections), and FP are the false positives (extra detections). Also, the absolute time difference $|\Delta t_{loc}|$ between the true location of the inserted crackle and the detected one with the smartphone app was quantified. Repeated measures analysis of variance (ANOVA) was employed to study the performance at each scenario with different SNR considering $p < 0.05$ as statistically significant.

III. RESULTS

An example of the TVAR coefficients estimation using the RLS algorithm implemented in the smartphone device is shown in Fig. 3 for an inspiration. It is possible to observe transients in the time course of the TVAR coefficients due to the presence of inserted crackles in the basal lung sounds.

Table I. Performance indices of the automated crackle detector implemented in the smartphone app (N=10).

Factor	Inserted crackles	TP	FN	FP	Accuracy	Sensitivity	$\|\Delta t_{loc}\|$ (ms)
Scenario 1: Early inspiratory fine crackles							
1.5	620	584	36	3	0.938 ± 0.025 *	0.942 ± 0.026 *	0.011±0.007 *
2.5	620	574	46	2	0.924 ± 0.026	0.927 ± 0.027	0.017±0.006
3.5	620	569	51	1	0.917 ± 0.026	0.918 ±0.026	0.021±0.006
Scenario 2: Late inspiratory fine crackles							
1.5	620	579	41	1	0.931±0.024 *	0.933±0.024 *	0.012±0.005 *
2.5	620	572	48	3	0.917 ±0.025	0.922±0.024	0.021±0.009
3.5	620	566	54	3	0.907 ± 0.032	0.912 ± 0.032	0.027±0.008
Scenario 3: Inspiratory fine crackles and expiratory coarse crackles							
1.5	1150	1079	71	2	0.936 ± 0.018 *	0.937 ± 0.020 *	0.023±0.005 *
2.5	1150	1084	66	2	0.940 ± 0.016	0.942 ± 0.017	0.025±0.005
3.5	1150	1056	94	2	0.917 ± 0.037	0.918 ± 0.039	0.019±0.003

Data presented as mean ± standard deviation for all sound recordings.
* indicates statistically significant effect of SNR on performance detection in that scenario

Results regarding the performance indices of the automated crackle detector are presented in Table I for the analyzed LS recordings with synthetic crackles inserted in the scenarios with different SNR. For each simulated scenario, statistically significant differences were found for the accuracy and sensitivity of the detector with different SNR, e.g., for the first scenario involving early inspiratory fine crackles, $F(2,18) = 10.091, p = 0.001$ and $F(2,18) = 10.676, p = 0.001$ for the accuracy and sensitivity, respectively. Similar results were found for the remaining two scenarios. Regarding the temporal difference between the true inserted and correctly detected crackle location, statistical significant differences were found due to SNR for each simulated scenario. Also, it was found that the maximum error was ± 1 sample (0.1 ms) where the median error was equal to 0 samples, for all simulated scenarios.

Finally, in Fig. 4 we include an example of the automated crackle detection results obtained with the proposed system when applied to respiratory sounds acquired from a patient with real crackles. Recording was performed at basal exterior right hemithorax (RBe) location where the pneumologist heard crackles during auscultation with the stethoscope. The acquired signal in the upper panel presents several spikes some of them corresponding to crackles. The system was able to detect the temporal position of real crackles (red dots). In the lower panel of Fig. 4, it is shown that the system in fact detects the crackle as it resembles the classical morphology and time durations described in the literature [2].

IV. DISCUSSION AND CONCLUSION

In this work, we present preliminary results regarding the development of a mCORSA system capable of automatically detect discontinuous adventitious lung sounds. The developed Android app was designed to allow the physician to record respiratory sounds via a friendly GUI that displays a guide of the respiratory maneuver to perform. Detection results can be presented to the user in terms of the respiratory sound waveform and crackle locations as well as in terms of a table summarizing the detection results for each portion of the respiratory phases.

It is currently recognized that the timing of respiratory crackles must be characterized as it has been found to reflect different pulmonary disorders [1], e.g., crackles in the late portion of inspiration and crackles in the early portion of inspiration have been associated with restrictive pulmonary diseases and severe airway obstruction, respectively. Although less frequently than inspiratory crackles, expiratory crackles can also be found in respiratory diseases. Hence, respiratory sound scenarios were simulated by inserting synthetic crackles to real acquired lung sounds at different noise levels. Detection of the inserted crackles was performed with an accuracy ranging from 90.7% to 94.0% and sensitivity ranging from 91.2% to 94.2% for the studied scenarios involving late and early inspiratory crackles and expiratory crackles. In general, there was a small reduction in the detection performance as the SNR increased. When correctly detected the estimated location of crackles only differs at most by 1 sample from the actual inserted location.

Figure 4. Automated crackle detection (red dots) in a recording from a patient with respiratory diseases using the proposed system.

The obtained results show the feasibility of implementing a portable system based on a smartphone able to detect respiratory crackles with different signal-to-noise ratios in scenarios found in clinical practice. Current work of our research group involves completing the recording of respiratory sounds from patients with respiratory diseases who exhibit crackles as well as the labeling of their locations that will help to validate the performance of the proposed mCORSA system in the clinical practice.

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