Monitoring Respiratory Sounds: Compressed Sensing Reconstruction via OMP on Android Smartphone

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Abstract. We present a novel respiratory sounds monitoring concept based on compressive sensing (CS). Respiratory sounds are streamed from a body-worn sensor node to a smartphone where processing is conducted. CS is used to simultaneously lower sampling frequency on the sensor node and over-the-air data rate. In this study we emphasize compressed sensing reconstruction via orthogonal matching pursuit (OMP) on Android smartphone. Accuracy of the reconstruction and execution speed are investigated using synthetic signals. We demonstrate applicability of the technique in real-time reconstruction of at least 10 components of compressible DCT spectrum of respiratory sounds containing asthmatic wheezing, acquired at 4x lower sampling rate.

Keywords: asthma, m-health, compressive sensing, orthogonal matching pursuit, smartphone, Android.

1 Introduction

Concept of patient-centric solution for long-term self-monitoring of chronic respiratory diseases, such as asthma was shown in [8]. The system featured monitoring of physiological functions via body-worn sensor nodes. Smartphone was proposed as an access point for the sensor nodes and for convenient interaction with the patient.

Seizures related to different chronic respiratory disorders exhibit occurrence of specific pathological sounds superimposed to the sound of normal breathing. In asthma, these are wheezes, signals continuous in duration, exhibiting concentration of energy into discrete sets of spectral crests (peaks) in frequency band of normal respiratory sound (100-1000 Hz) [7]. Purpose of long-term physiological function monitoring is quantification of occurrence and durations of portions of respiratory cycles occupied by wheezing.

Capture of such information consists of acquisition of respiratory sounds via microphone or accelerometer and signal processing in order to classify breathing sounds into a normal or pathological class. In order to fulfil the requirement

B. Godara and K.S. Nikita (Eds.): MobiHealth 2012, LNICST 61, pp. 114–121, 2013.

of long-term operation, energy consumption needs to be minimized. Analysis of energy consumption of the sensor node [9] identified two feasible approaches. The first includes intensive signal processing on body-worn node at the signal acquisition site, and transmission of the classification result to the smartphone for logging and/or presentation. Advantage of such approach is reduced load on the communication subsystem. Disadvantages are the higher energy consumption of the sensor node and higher cost of software maintenance/upgrade.

The alternative approach is streaming the signal to smartphone where processing is performed. Such approach enables lower power design of the sensor node and simplifies maintenance of software by moving signal processing into the domain of smartphone mobile applications development. On the other side, in this approach the quality of information is heavily dependent on the communication link between the sensor node and the smartphone. Also, energy costs of both communication and signal processing on the smartphone can be high.

Compressive sensing (CS) enables simultaneous reduction of energy cost in both acquisition and communication part on the sensor side by lowering data rate, as seen in [3] where CS is applied in a wireless sensor network for frequency-sparse signal detection. Implementations of CS reconstruction algorithms for popular smartphone platforms can be found in [4]. [6] and [5] have shown reconstruction of streamed CS electrocardiogram signal. In this article, we present our work on reconstruction of respiratory sounds on an Android smartphone, part of the CS-based asthma monitoring system shown in Fig. 1. So far, we experimented with "orthogonal matching pursuit" (OMP) iterative reconstruction algorithm [10].

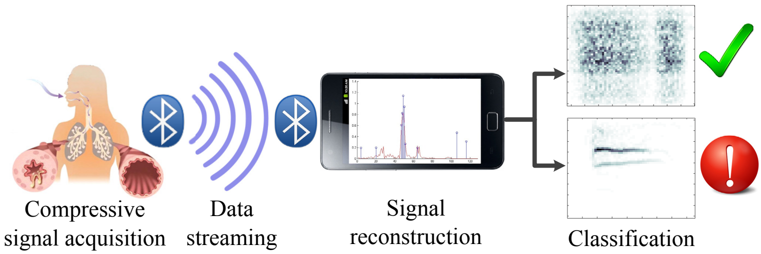


Fig. 1. Architecture of the asthma monitoring system

2 Methods and Materials

2.1 Compressed Sensing Paradigm

Let $\mathbf{x} = \{x_1, ..., x_N\}^T$ be an N-dimensional column vector representing samples of time-discrete signal acquired by the sensor node. Suppose that x can be represented by only $K << N$ non-zero components $\{\theta_1, ..., \theta_K\}$ when transformed by suitable transformation matrix $\mathbf{\Psi}$, as shown by (1):

$$\theta = \mathbf{\Psi x}. \tag{1}$$

Compression of N-dimensional signal $\mathbf{x}$ to the M-dimensional vector $\mathbf{y}$, $M < N$ is performed on the sensor node by inner product of rows (i.e. *measurement vectors*) of $M \times N$ dimensional measurement matrix $\mathbf{\Phi}$ and signal $\mathbf{x}$:

$$\mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi \Psi^{-1}}\theta. \tag{2}$$

Vectors of compressed data $\mathbf{y}$ are streamed over a wireless link to the smartphone. The original signal, represented by its sparse coefficients estimates $\hat{\theta}$, is obtained by solving an undetermined system (3). Compressive sensing theory states that the good estimate of a sparse solution is the one with minimal $l1$-norm:

$$\hat{\theta} = argmin||\mathbf{z}||_1,\ subject\,to\,\mathbf{y} = \mathbf{\Phi \Psi^{-1} z}. \tag{3}$$

2.2 Orthogonal Matching Pursuit Algorithm

The premise of the algorithm is that as θ is K-sparse, only K of N columns-vectors $\{\varphi_1, ..., \varphi_N\}$ of $\mathbf{\Phi \Psi^{-1}}$ participate in the compressed signal $\mathbf{y}$. Algorithm searches for the column φ_j most highly correlated to $\mathbf{y}$ and uses it to calculate a signal estimate $\hat{\theta}$ by solving associated over-determined system by least-squares method. Residual of $\mathbf{y}$ is found and the algorithm advances to the next iteration until K components are found.

We evaluate straight-forward implementation described in [10] on Android smartphone, using Java and Android SDK. Matrix operations, including least-squares algorithm were implemented using Efficient Java Matrix Library (EJML) [1]. All tests described in the following sections were performed on a Samsung Galaxy S2 device running Android OS v2.3.5 and were compared against referent implementation in Matlab [2].

2.3 Testing

Testing was conducted in three parts. In the first part we evaluated the accuracy of signal reconstruction. Secondly, the execution speed was tested. Finally, the algorithm was tested on respiratory sound signals.

Reconstruction Error. Reconstruction error was evaluated against signal sparsity K, and compressed signal lengths M for the fixed signal block length of $N = 256$ samples. Similar test-setup as in [10] was used: 1-s on random indices were used as sparse input signal. As a measurement matrix, a dense random matrix of uniformly distributed ± 1 values was used. Identity transformation matrix was used, because input signal was already sparse. Experiment was repeated 100 times for different combinations of N, M and K.

Two metrics for reconstruction error evaluation were used. First was the percentage of reconstructed signal blocks in which all samples have been reconstructed on correct indices. Goal was to measure the similarity to referent OMP algorithm by evaluating occurrence of estimates at incorrect indices when sparsity K becomes too large or compressed signal length M too short compared to original signal length N. The second metric was the accuracy of amplitude reconstruction, measured by normalized $l2$-error (4), averaged over all repetitions of the experiment.

$$Err = \frac{||\hat{x} - x||_2}{||x||_2} \tag{4}$$

Execution Speed. OMP guarantees deterministic execution time. It breaks down the problem of solving an under-determined system of M equations and N unknowns to a set of K least squares problems of order t which is increasing by each iteration $t_1, ..., t_K$.

Dependency of execution time was verified for signal length $N = \{128, 256, 1024\}$, signal compression ratios of $4\times$ and $8\times$ and signal sparsity of $K = \{2, ...30\}$. Android method $System.nanoTime()$ was used for time measurement. Results were averaged over 300 repetitions.

Respiratory Sounds. In order to test recovery of both compressible spectrum of wheezing and broadband spectrum of normal breathing, $N \times N$ inverse discrete cosine transform (IDCT) matrix $\mathbf{\Psi}$ was used as a transformation matrix. Sparse measurement matrix $\mathbf{\Phi}$ containing uniformly distributed discrete set of $\{0, 1\}$ was used, effectively defining a mask for random selection of M out of N rows of IDCT matrix. At the same time, indices of 0-s in $\mathbf{\Phi}$ define which of the (discrete) time-domain samples can be omitted from sampling.

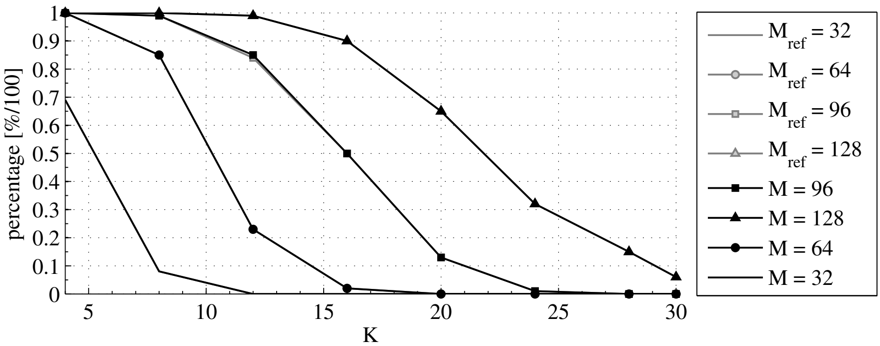
Pre-recorded respiratory sounds acquired from various Internet sources (such as R.A.L.E.) were used as input signals. The dataset consisted of 10 recordings N01...N10 of normal respiratory sounds (total duration 76 s), and 12 recordings W01...W12 of wheezing (in total 44 s). Each recording originated from a different patient. Intervals of intra-respiratory silence and normal breathing were removed from W01...W12 in order to produce continuous sections of signal compressible in frequency. All recordings were bandpass-filtered to 100-1000 Hz, resampled to Nyquist frequency of 2048 samples/s, normalized by amplitude, and segmented into blocks of $N = 256$ samples.

This test was repeated 100 times on each N-block of every recording, with combinations of parameters $M = \{64, 128\}$ and $K = 10$. Results were evaluated by three metrics. The first was the accuracy of reconstruction of amplitudes, measured by normalized $l2$-error as already described by (4). Remaining two metrics address frequency-locations (indices) of reconstructed spectral samples: percentage of indices reconstructed within set of frequencies containing 90 % of energy of original DCT spectrum, and percentage of reconstructed samples exhibiting grouping of two or more indices in an uninterrupted sequence. Results were averaged over all repetitions of the same signal-block, and furthermore over all blocks within each recording.

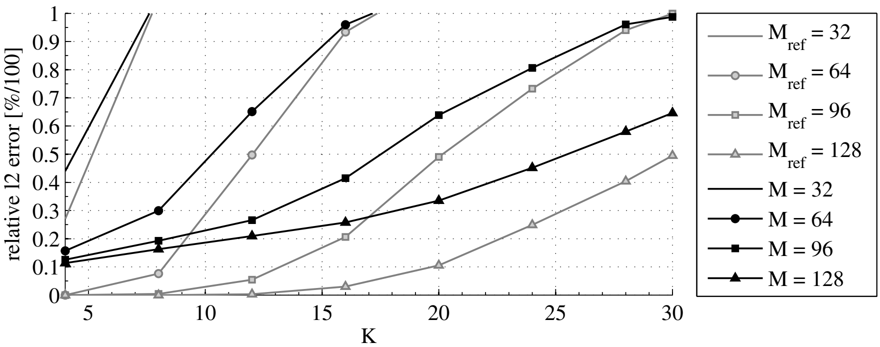
3 Results

3.1 Accuracy

Fig. 2(a) shows good fit between our implementation and the referent OMP from Matlab. On the other hand, Fig. 2(b) shows worse fit when examining $l2$-error (4). For the case of relaxed conditions of reconstruction, (lower signal sparsity K, lower compression rate/higher M), $l2$-error of our algorithm converges to a value of around 10 %. Nevertheless, relations between N, M and K obey terms stated by CS theory. It can be seen that at 30 % reconstruction error, maximum obtainable compression rate $N/M = 4$ with 8 components recovered, or alternatively 16 components can be recovered at $N/M = 2$.



(a) Percentage of blocks with all data reconstructed at correct indices, $N = 256$.



(b) Error of amplitude estimation, $N = 256$.

Fig. 2. Accuracy of signal reconstruction by our version of OMP executed on Android, compared to referent OMP implementation, both tested on an identical data set

3.2 Execution Speed

Results corroborating the expected theoretical relations are visualized in Fig. 3. It is interesting to notice that higher compression ratios N/M, apart from increasing energy saving in communication, also shorten execution of reconstruction of the same targeted number of components K proportionally.

Let's evaluate constraints for real-time operation on respiratory sounds. If the sampling rate of the original time-domain signal was 2 kHz, block-size was $N = 256$ and a 50 % block overlap was used, duration between subsequent blocks would be 64 ms. As seen from Fig. 3, at most $K = 10$ components could be recovered in real-time at $N/M = 4$. The time for real-time construction of measurement matrix is not considered.

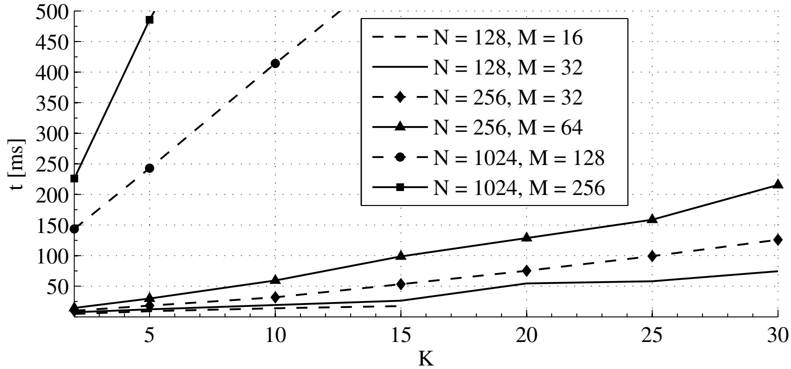
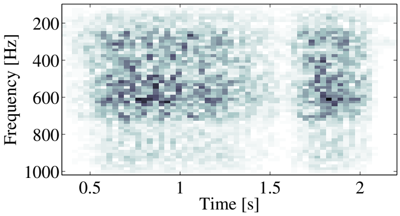


Fig. 3. Duration of execution versus N, M and K, measured on Samsung Galaxy S2

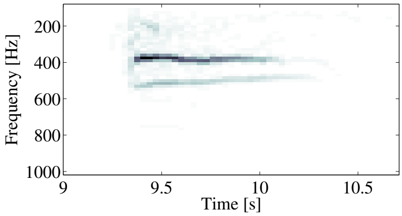
3.3 Reconstruction of Respiratory Signals Spectra

Characteristic reconstruction examples of DCT spectrum blocks originating from normal and wheezy signals shown in Figs. 4(a) and 4(b) can be compared in Figs. 4(c) and 4(d). Several effects can be observed, justifying the choice of three metrics described in Section 2.3. Most obvious is the grouping of reconstructed samples at spectral crest frequencies of the wheeze, and less evident for broadband normal breathing. Also, two side-effects arise: reconstruction of frequencies beyond those containing most of signal block energy, and error of amplitude/energy estimation.

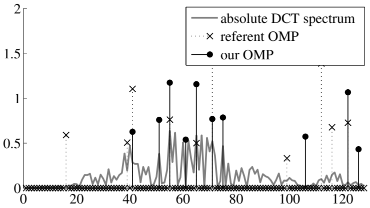
Overall results are shown in Fig. 5. Percentage of indices reconstructed within 90 % of the energy of an original DCT block decreases with M for both normal and wheezy respiratory signals. Relative $l2$-error ceases with increase of M, with wheezes exhibiting lower error, as a consequence of higher accuracy of estimation of high energy wheeze crests. Percent of grouped indices rises with M, and is higher for compressible spectrum of wheezing.



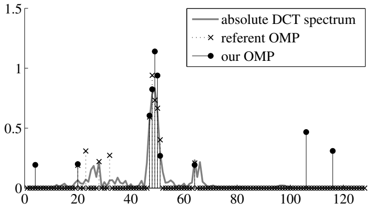
(a) Spectrogram, normal (N08)



(b) Spectrogram, wheezing (W07)

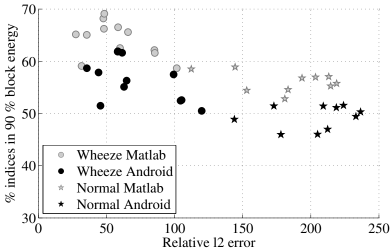


(c) Reconstruction, normal breathing

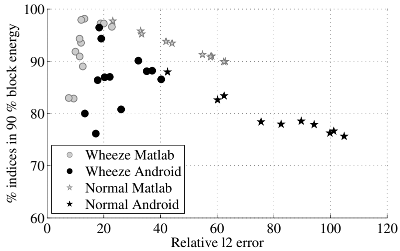


(d) Reconstruction, wheezing

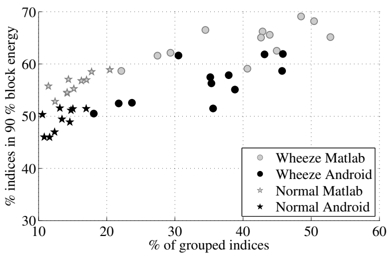
Fig. 4. Examples of DCT reconstructed by OMP for single block of normal respiratory signal and block with wheezing ($N = 128$, $M = 32$, $K = 10$)



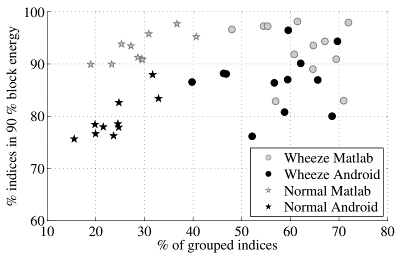
(a) $M = 64$



(b) $M = 128$



(c) $M = 64$



(d) $M = 128$

Fig. 5. Overall comparison of DCT spectrum reconstruction accuracy on data sets N01...N10 and W01...W12, $N = 256$, $K = 10$

4 Conclusion

Our implementation of OMP algorithm was shown. Results were compared to referent OMP algorithm in Matlab. Compression ratio of at least 4× can be achieved in reliable reconstruction of 10 frequency components for signal-block lengths of 256 samples in real-time on a smartphone, as demonstrated on spectrum of frequency-compressible respiratory signals. Drawbacks of current implementation are low accuracy of amplitude estimation, and operation on real matrices only. In the future we plan to extensively evaluate CS sampling setups and further investigate tradeoff between accuracy and execution speed of other CS algorithms. Reconstruction algorithm is to be accompanied by a suitable classification algorithm using features drawn from the reconstructed spectrum.

Acknowledgment. This study is supported by RECRO-NET through the *Biomonitoring of physiological functions and environment in management of asthma* project conducted at University of Zagreb, Faculty of Electrical Engineering and Computing.

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