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Characterization of infant healthy and pathological cry signals in cepstrum domain based on approximate entropy and correlation dimension

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ABSTRACT

The analysis of infant cry signals is becoming an attractive field of research in biomedical physics and engineering for better understanding of the pathologies and appropriate medial diagnosis. The main purpose of the current study is to characterize infant normal and pathological cry signals by studying their respective oscillations by means of approximate entropy and correlation dimension estimated from their respective cepstrums. We analyzed two different sets. The first one is composed of 2638 expiration cry signals and the second set is composed of 1860 inspiration cry signals, both sets equally weighted. After estimating approximate entropy and correlation dimensions from cepstrums, three standard statistical tests are applied to them including the Student *t*-test, *F*-test, and two-sample Kolmogorov-Smirnov test. All statistical tests are performed at 5% statistical significance level. The empirical results follow. First, approximate entropy and correlation dimension measures exhibit different statistical characteristics across healthy and unhealthy infant cries from both expiration and inspiration sets. Second, the level of approximate entropy in cepstrums of healthy infant cries is statistically higher than that in cepstrums of unhealthy infant cries. Third, the level of correlation dimension in cepstrums of healthy infant cries is statistically higher than that in cepstrums of unhealthy infant cries. In other words, cepstrums of healthy infant cries show lower randomness and disorder compared to cepstrums of unhealthy infant cries. It is concluded that cepstrum-based approximate entropy and correlation dimension discriminate healthy from pathological infant cry signals and can be employed as effective biomarkers for biomedical diagnosis of cry records in clinical milieu.

1. Introduction

In recent years, there is a growing interest in the diagnosis of cry signal to detect pathology in unhealthy infants. Indeed, the acoustical analysis of infant cry signal is independent of human intervention, helpful to assess pain in paediatric wards; and, consequently, can assist clinicians in medical decision-making. In this regard, various automatic diagnosis systems have been proposed where infant cry signal have been analyzed by means of melody, rhythm short-term features, and mel-frequency cepstral coefficients [1,2,3], standard acoustic parameters [4], fundamental frequency glide and resonance frequencies dysregulation [5], resonance frequency averages, durations, and transitions [6], and wavelet packet transform based energy and entropies [3].

The main purpose of the current work is to examine the statistical discriminative power of cepstrum-based complexity measures in distinguishing between healthy and pathological infant cry signals. Indeed, such investigation is expected to help understanding the nonlinear dynamics in healthy and pathological infant cry signals to better distinguish between them by physicians in clinical milieu. Without a doubt, shedding light on complexity in dynamics of cry-recorded sounds would be a benefit in the design of automatic systems for cry signal diagnosis to increase accuracy of diagnosis and reduce time of medical consultation. In short, an objective nonlinear statistical analysis can only be used as an assistive

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tool by clinicians who definitively have the final decision regarding the medical diagnosis.

It is worth to notice that pathological samples have a strong tendency for frequent and rapid changes in regularity [7] and that pathological voices tend to show unusually large cycleto-cycle fluctuations [8]. In this regard, the analysis of infant cry signals by means of cepstrum [9] is suitable to detect intrinsic periodicity and rapid oscillations. Besides, approximate entropy [10] and correlation dimension [11,12] are two complexity measures that will be estimated from the cepstrum to better characterize each infant cry signal. In one hand, approximate entropy is a measure of regularity to quantify levels of complexity within a nonlinear signal where variability is defined through examination of the temporal variations in it. On the other hand, based on phase space reconstructions, correlation dimension, which is an example of fractal dimension, is capable to reveal structure in a nonlinear signal when compared with a random process.

The ability to discern levels of complexity within physiological signals has become increasingly important. For instance, approximate entropy was used to characterize surface electromyographic signals [13], cardiac synchrony [14], gait rhythm [15], and epileptic seizure [16,17]. In addition, correlation dimension was successfully used to analyze electroencephalogram records [18,19], heart rate variability [20,21], epileptic seizures [22], and organization of resting state cortical networks [23]. Furthermore, the correlation dimension was employed in electroencephalogram compression and transmission in clinical milieu [24].

The contributions of the current work follow. First, while recent works [1-6] focused on classification of infant cries, the current study conducts a deep statistical analysis on the discriminative power of two main complexity measures in distinguishing between healthy and unhealthy infant cry signals. Second, for robustness of the results, a large dataset is examined, contrary to previous works [1-6] where relatively small samples were used. Third, statistical analyses will be applied to both inspiration and expiration signals recorded from healthy and unhealthy infants. Fourth, the study will reveal the nonlinear characteristics of healthy and healthy infant inspiration and expiration signals. As a result, one would better understand the nonlinear dynamics of such signals from healthy and unhealthy infant populations. Fifth, eventually, the results are expected to help physicians in decision-making in clinical milieu.

The rest of the paper is organized as follows: Section 2 introduces the cepstrum analysis, approximate entropy, and correlation dimension. Section presents data and results. Finally, Section 4 concludes the study.

2. Methods

In this study, we seek to characterize each single cry (inspiration/expiration) record by combining cepstrum analysis with complexity measures. In particular, cepstral analysis is applied to the original cry record to obtain its cepstrum. Then, approximate entropy and correlation dimension are estimated from the resulting cepstrum. Afterward, three formal statistical tests will be performed; namely, the Student *t*-test, *F*-test, and two-sample Kolmogorov-Smirnov test to check respectively equality of means, variances, and similarity of distributions in approximate entropy and correlation dimension across cry cepstrums of healthy and unhealthy infants. All statistical tests will be performed at 5% statistical significance level. Indeed, such different statistical tests are expected to verify whether approximate entropy and correlation dimension are different across healthy and unhealthy infants. If they are, then would help understanding the nonlinear dynamics in infant cries, and eventually be used as biomarkers.

Finally, it is worth to mention that we rely on entropy and correlation dimension measures because they were effective in biomedical physics and engineering applications [13-24] and in various science and engineering problems [25-29].

2.1. Cepstrum analysis

Cepstral analysis was initially developed in the field of homomorphic deconvolution [9]. For instance, the complex cepstrum $\hat{s}(n)$ of a signal $s(n)$ is given by the inverse Fourier transform of its log spectrum as follows:

$$\hat{s}(n) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \ln S\left(e^{J\omega}\right)\, e^{J\omega n} d\omega \tag{1}$$

where, $S(e^{J\omega})$ is the discrete Fourier Transform of s(n) and is given by:

$$S\left(e^{J\omega}\right) = \sum_{n=-\infty}^{\infty} s(n)e^{-J\omega n} = \left|S\left(e^{J\omega}\right)\right| e^{J\theta(\omega)} \tag{2}$$

where $|S(e^{J\omega})|$ and $\theta(\omega)$ are respectively the amplitude and the phase spectra.

Besides, the real cepstrum of a signal takes into consideration only its amplitude spectrum. Specifically, the real cepstrum $\hat{r}(n)$ of a signal $s(n)$ is given by:

$$\hat{r}(n) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \ln \left|S\left(e^{J\omega}\right)\right|\, e^{J\omega n} d\omega \tag{3}$$

In this work, the real cepstrum will be calculated from healthy and pathological infant cry records. Then, approximated entropy and correlation dimension will be estimated from the obtained real ceptrums to characterize healthy and pathological infant cry records. The approximated entropy and correlation dimension are presented next.

2.2. Approximate entropy

The approximate entropy [10] is a nonlinear statistic used which is appropriate to quantify the regularity/irregularity of a nonlinear signal. Additionally, it provides efficient statistical estimates even the original signal length is small [10]. Let consider a time series $\langle x(n) = x(1), x(2), x(3), \ldots, x(N)\rangle$ where N is the time series length. Let m be a positive integer used to represent an embedding dimension and let r be a filter factor. Then, let form the m-vectors $X(1), X(2),\ldots, X(N-m+1)$ where $X(i)=[x(i), x(i+1),\ldots, x(i+m-1)]$ and $i=1, N-m+1$. The distance between $X(i)$ and $X(j)$ is expressed as follows:

$$d[X(i), X(j)] = \max_{k=0,m-1}\left[|x(i+k) - x(j+k)|\right] \tag{4}$$

Then, for each $i=1, (N-m+1)$, the $C_r^m(i)$ are computed where:

$$C_r^m(i) = \frac{number\ of\ d[X(i), X(j)] \le r}{N-m+1} \tag{5}$$

Then, the quantity $\Phi^m(r)$ is computed as follows:

$$\Phi^m(i) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} log(C_r^m(i)) \tag{6}$$

In a similar way, the quantity $\Phi^{m+1}(r)$ is computed after increasing the dimension to m+1. Finally, the *ApEn* value of the time series can be calculated by:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \tag{7}$$

Recall that a large value of *ApEn* represents strong irregularity of the current time series. In contrary, a low *ApEn* value implies regularity.

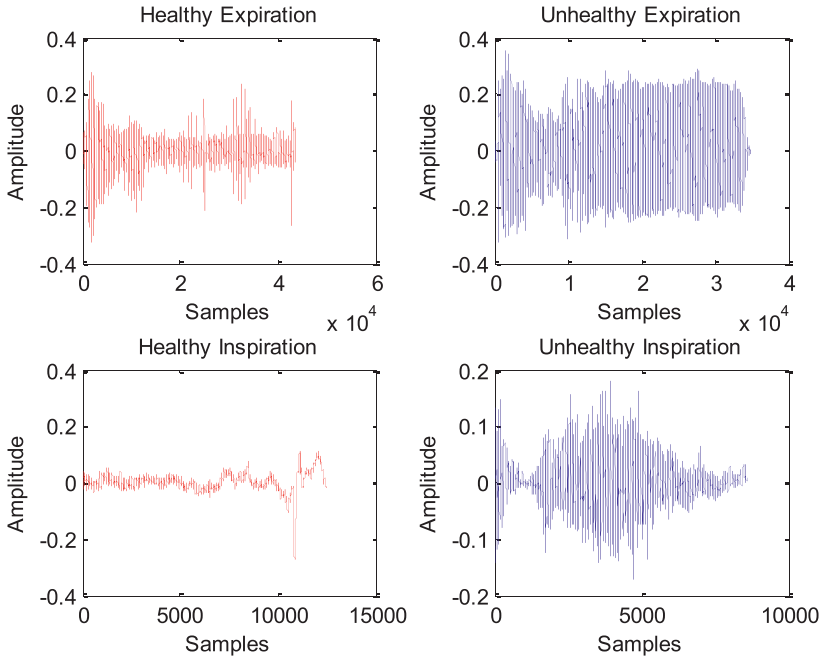

Fig. 1. Example of healthy and unhealthy cry signals.

2.3. Correlation dimension

The Correlation Dimension (CD) of a given time series is effective in providing an unbiased estimator of the intrinsic dimension [30]. In this paper, the CD is estimated based on the efficient Grassberger-Procaccia algorithm [11,12]. For instance, the CD is measured by calculating correlations between points of a time series on the attractor [2,3]. First, let divide the signal x to be analyzed into m dimensions. The m dimensional vectors are expressed as follows:

$$Y_1 = \left(X_1, X_{1+\tau}, \ldots, X_{1+(m-1)\tau}\right) \tag{8}$$

$$Y_2 = \left(X_2, X_{2+\tau}, \ldots, X_{2+(m-1)\tau}\right) \tag{9}$$

$$Y_N = \left(X_N, X_{N+\tau}, \ldots, X_{N+(m-1)\tau}\right) \tag{10}$$

where N is the number of vectors, m is the embedding dimension, and τ is the time delay of the reconstructed phase space. In general, Time delay is calculated by taking the first minimum of the autocorrelation function and the embedding dimension is calculated by using the nearest neighbor algorithm. Then, the correlation integral $C_m(r)$ is computed as follows:

$$C_m(r) = \frac{2}{(N(N-1))} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \Theta\left(\left\|Y_i - Y_j\right\| - r\right) \tag{11}$$

where Θ is the Heaviside function given by:

$$\Theta(u) = \begin{cases} 0 & if\ u \le 0 \\ 1 & if\ u > 0 \end{cases} \tag{12}$$

Here, $u = (\|Y_i - Y_j\| - r)$ and $\|Y_i - Y_j\|$ is the distance between two reconstructed vectors and r is the distance parameter. Recall that $C_m(r)$ represents the power law expressed as follows:

$$C_m(r) \sim r^{CD} \tag{13}$$

Hence, the correlation dimension (CD) is approximated as follows:

$$CD \equiv \lim_{r \to 0} \frac{log(C_m(r))}{log(r)} \tag{14}$$

Finally, the slope of the log-log plot of $C_m(r)$ versus r represents CD. In our study, the embedding dimension was set to two. It was calculated by using the false nearest neighbor algorithm [31] which is an efficient computational method.

3. Data and results

The database is composed of two sets: expiration (EXP) set and inspiration (INS) set. The EXP set has 2638 cry signals and INS set has 1860 cry signals. Specifically, there are 1319 healthy signals and 1319 unhealthy signals in the EXP set. Besides, there are 930 healthy signals and 930 unhealthy signals in the INS set. To record cry signals, a two-channel sound recorder with a sampling frequency of 44.1 kHz and a resolution of 16 bits was placed at 10cm to 30cm from the infant. The time duration of each recorded signal is within 2–3 min. Each original recorded cry signal has been pre-processed to remove background noise and artifacts. It is also segmented to keep only respiration and expiration episodes. The segmentation task is manually performed by using the Wave Surfer tool.

All infant cry signals have been recorded in the neonatology departments of the following hospitals: Sainte-Justine hospital (Montreal, Canada), and Al-Sahel and Al-Raee hospitals, both in Lebanon. The infants who entered the study are preterm and full term and their respective ages range from 1 to 53 days. The sample includes both healthy and unhealthy babies and both males and females. The group of unhealthy babies suffers from various pathologies such as diseases affecting the central nervous system, and respiratory system. Other pathologies include blood disorder, chromosomal abnormality, and congenital cardiac anomaly. For illustration purpose, Fig. 1 displays examples of healthy and unhealthy signals. Examples of cepstrums representing healthy and unhealthy cry signals are shown in Fig. 2 where each cepstrum has a size of 1000 data points.

The distributions of the estimated approximate entropy measures across healthy and unhealthy infant cries for expiration and inspiration sets are exhibited in boxplots shown in Fig. 3. Similarly, the boxplots of estimated correlation dimension measures are displayed in boxplots shown in Fig. 4. As observed, the distributions

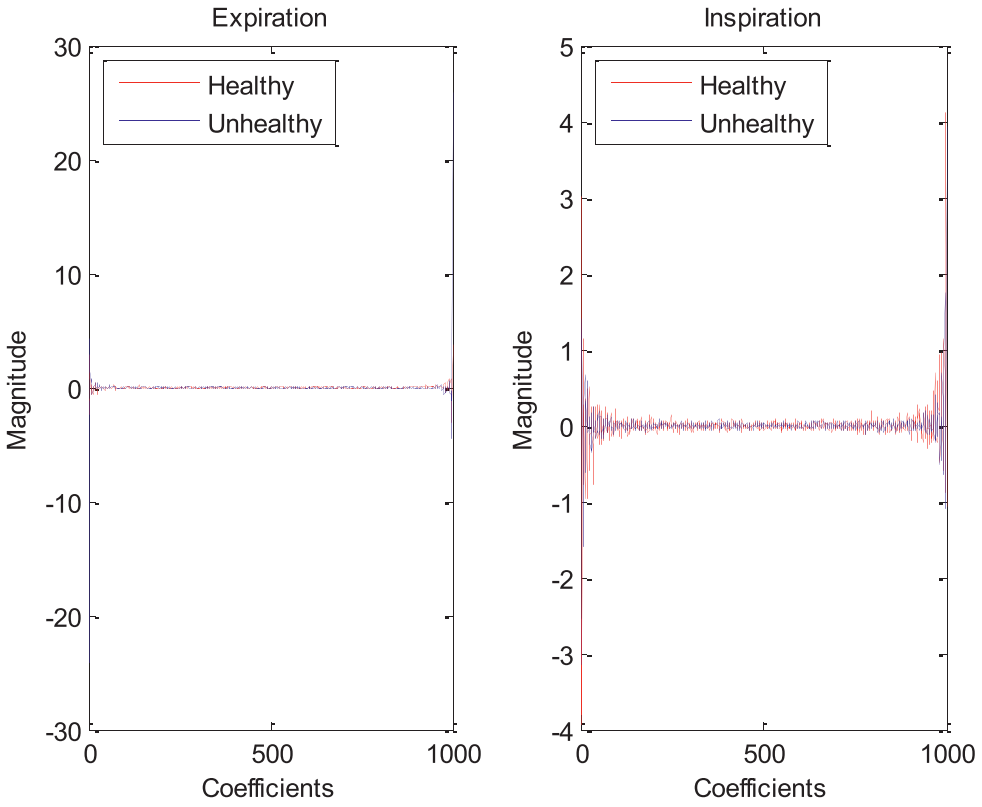

Fig. 2. Examples of cepstrums from healthy and unhealthy infant cry signals.

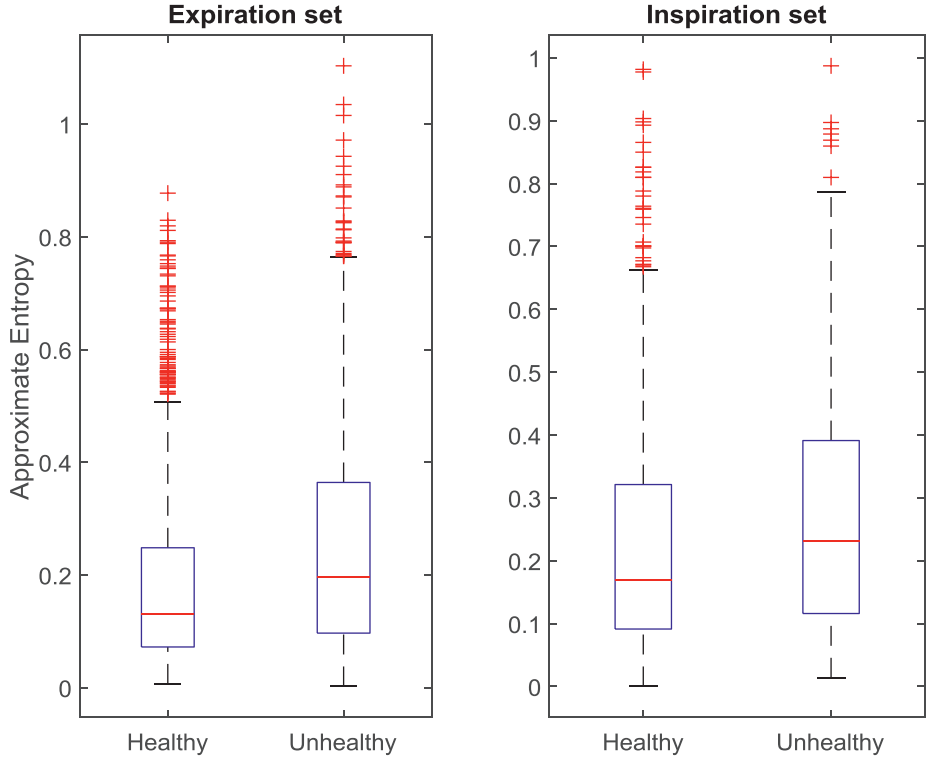

Fig. 3. Boxplots of estimated approximate entropy measures.

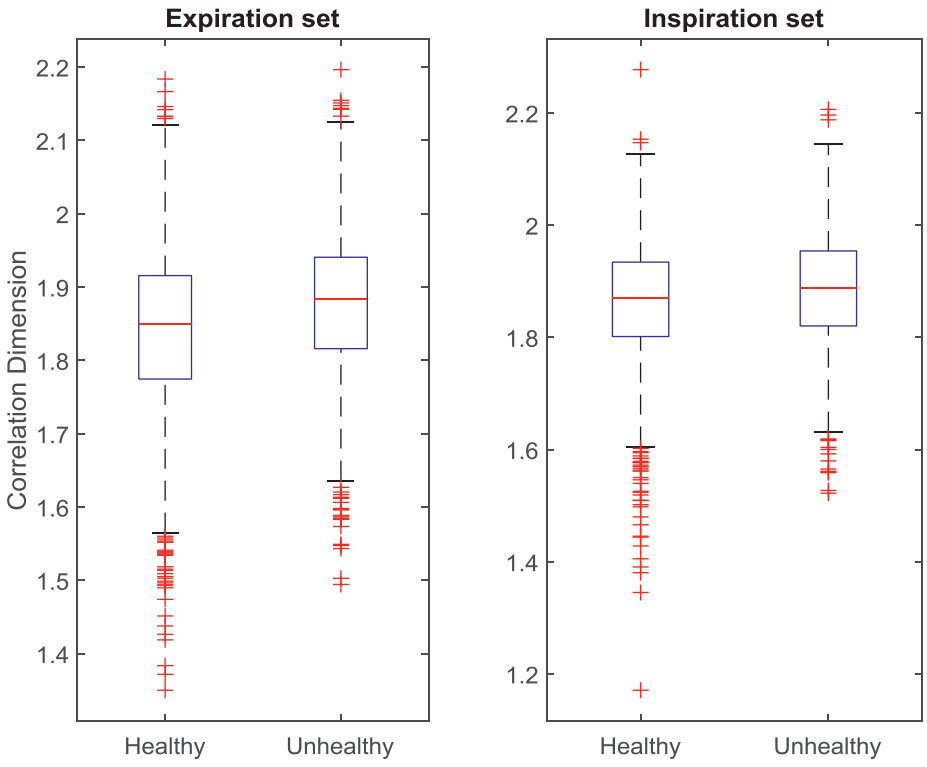

Fig. 4. Boxplots of estimated correlation dimension measures.

Table 1
Reported *p*-values from statistical tests applied to estimated approximate entropy measures from healthy and unhealthy infant cries.

	Null hypothesis	Expiration set	Inspiration set
Student *t*-test	Equality of the means	3.0839×10^{-22}	1.5994×10^{-07}
***F*-test**	Equality of the variances	2.8776×10^{-15}	0.0973
Kolmogorov-Smirnov test	Similarity of distributions	1.4178×10^{-19}	8.7991×10^{-09}

All tests are performed at 5% statistical significance level. A *p*-value less than 5% yields to rejection of the null hypothesis.

Table 2
Reported *p*-values from statistical tests applied to correlation dimension measures from healthy and unhealthy infant cries.

	Null hypothesis	Expiration set	Inspiration set
Student *t*-test	Equality of the means	6.9589×10^{-19}	2.7113×10^{-07}
***F*-test**	Equality of the variances	7.7999×10^{-06}	1.4517×10^{-05}
Kolmogorov-Smirnov test	Similarity of distributions	1.8512×10^{-13}	9.2822×10^{-04}

All tests are performed at 5% statistical significance level. A *p*-value less than 5% yields to rejection of the null hypothesis.

of approximate entropy measures and correlation dimension measures are clearly different across healthy and unhealthy infants under both expiration and inspiration sets. The results from formal statistical tests in terms of calculated probability value (*p*-value) are reported in Tables 1 and 2 for approximate entropy and correlation dimension respectively.

According to Table 1, the Student *t*-test strongly rejects the null hypothesis for equality of means of approximate entropy in healthy and unhealthy infants under both expiration and inspiration sets. Similarly, the Kolmogorov-Smirnov test strongly rejects the null hypothesis of similarity of distributions of approximate entropy between healthy and unhealthy infants under both expiration and inspiration sets. Besides, the *F*-test shows that variances of approximate entropy across healthy and unhealthy infants are equal in expiration set. However, they are not equal in inspiration set. Following the results of statistical tests presented in Table 1, the Student *t*-test strongly rejects the null hypothesis for equality of means of correlation dimension in healthy and unhealthy infants under both expiration and inspiration sets.

Similarly, according to Table 2, the *F*-test strongly rejects the null hypothesis of similarity of distributions of correlation dimension between healthy and unhealthy infants under both expiration and inspiration sets. In addition, the Kolmogorov-Smirnov test strongly rejects the null hypothesis of similarity of distributions of correlation dimension between healthy and unhealthy infants under both expiration and inspiration sets.

In short, the results from statistical tests presented in Tables 1 and 2 indicate that approximate entropy and correlation dimension measures exhibit different statistical characteristics across healthy and unhealthy infant cries from both expiration and inspiration sets. Lastly, it is interesting to check whether the level of these complexity measures varies through healthy and healthy

infants. In this regard, one-tailed t-test is applied to estimated approximate entropy and correlation dimension measures at 5% significance level.

The one-tailed t-test results from expiration set rejects the null hypothesis that the mean of approximate entropy in healthy infant is larger than that in unhealthy infants (p-value $= 1.5419 \times 10^{-22}$). Similarly, the one-tailed t-test results from inspiration set rejects the null hypothesis that the mean of approximate entropy in healthy infant is larger than that in unhealthy infants (p-value $= 7.9970 \times 10^{-8}$). Therefore, in both expiration and inspiration sets, the level of approximate entropy in cepstrums of healthy infant cries is strongly and statistically lower than that in cepstrums of unhealthy infant cries.

Besides, the one-tailed t-test results from expiration set rejects the null hypothesis that the mean of correlation dimension in healthy infant is larger than that in unhealthy infants (p-value $= 3.4794 \times 10^{-19}$). Similarly, the one-tailed t-test results from inspiration set rejects the null hypothesis that the mean of correlation dimension in healthy infant is larger than that in unhealthy infants (p-value $= 1.3556 \times 10^{-7}$). Therefore, in both expiration and inspiration sets, the level of correlation dimension in cepstrums of healthy infant cries is strongly statistically lower than that in cepstrums of unhealthy infant cries.

In summary, our nonlinear statistical analysis of cepstrums of healthy and unhealthy infant cries reveals that:

a) Approximate entropy and correlation dimension measures of cesptrum exhibit different statistical characteristics across healthy and unhealthy infant cries from both expiration and inspiration sets.
b) The level of approximate entropy in cepstrums of healthy infant cries is statistically higher than that in cepstrums of unhealthy infant cries. Hence, cepstrums of healthy infant cries show lower randomness compared to cepstrums of unhealthy infant cries.
c) The level of correlation dimension in cepstrums of healthy infant cries is statistically higher than that in cepstrums of unhealthy infant cries. Therefore, cepstrums of healthy infant cries show lower instability compared to cepstrums of unhealthy infant cries.

It follows from the results that the characteristics of the distributions of approximate entropy and correlation dimension carry valuable information in discriminating between pathological and normal cry cepstrums. Specifically, mean, variance and distribution similarity are useful to capture a full picture of the analyzed infant cry signal. In other words, these findings show that the investigated descriptive statistics for cepstrum-based approximate entropy and correlation dimension distributions as possible indicators of cry health status. Finally, it is worth to notice that since the main purpose of the work is to extract nonlinear features from infant cry records to distinguish between healthy and unhealthy infants, performing a surrogate analysis is not required for characterization of records and for the subsequent automatic classification task.

4. Conclusion

The clinical diagnosis of unhealthy infants by analysis of their cries is a non-invasive approach which is becoming attractive in biomedical physics and engineering. Indeed, voice performance is one of the several human functional operations that are affected by disease.

The aim of the current study was to investigate the ability of approximate entropy and correlation dimension estimated in cepstrum domain to characterize infant cry signal. In particular, to check whether cepstrum-based approximate entropy and correlation dimension are different across healthy and unhealthy infant cries, statistical tests were performed by using the Student t-test, F-test, rank sum test, and two-sample Kolmogorov-Smirnov test. The level of significance was set at $p \leq 0.05$. The results reveal that differences in statistical shapes of approximate entropy and correlation dimension, in most cases, are statistically different between the groups of cry cepstrums. More importantly, cepstrums of healthy infant cries show higher approximate entropy level than those of pathological infants. Similarly, cepstrums of healthy infant cries show higher correlation dimension level than those of pathological infants. To be specific, cepstrums of healthy infant cries show lower randomness and disorder compared to cepstrums of unhealthy infant cries. As a result, sample entropy and correlation dimension estimated in Fourier domain provide reliable statistical results for discriminating healthy from pathological voices.

In conclusion, this study indicated that the cepstrum-based approximate entropy and correlation dimension are statistically robust as biomarkers and could potentially be used in the diagnosis of healthy and pathological infant cries.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Salim Lahmiri: Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Chakib Tadj:** Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Christian Gargour:** Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Stelios Bekiros:** Conceptualization, Methodology, Software, Data curation, Writing - original draft.

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