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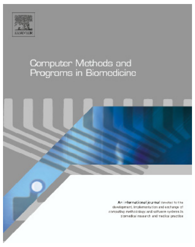

Assessment of time–frequency representation techniques for thoracic sounds analysis

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ABSTRACT

A step forward in the knowledge about the underlying physiological phenomena of thoracic sounds requires a reliable estimate of their time–frequency behavior that overcomes the disadvantages of the conventional spectrogram. A more detailed time–frequency representation could lead to a better feature extraction for diseases classification and stratification purposes, among others. In this respect, the aim of this study was to look for an omnibus technique to obtain the time–frequency representation (TFR) of thoracic sounds by comparing generic goodness-of-fit criteria in different simulated thoracic sounds scenarios. The performance of ten TFRs for heart, normal tracheal and adventitious lung sounds was assessed using time–frequency patterns obtained by mathematical functions of the thoracic sounds. To find the best TFR performance measures, such as the 2D local (ρ_{mean}) and global (ρ) central correlation, the normalized root-mean-square error (NRMSE), the cross-correlation coefficient (ρ_{IF}) and the time–frequency resolution ($\mathrm{res}_{\mathrm{TF}}$) were used. Simulation results pointed out that the Hilbert–Huang spectrum (HHS) had a superior performance as compared with other techniques and then, it can be considered as a reliable TFR for thoracic sounds. Furthermore, the goodness of HHS was assessed using noisy simulated signals. Additionally, HHS was applied to first and second heart sounds taken from a young healthy male subject, to tracheal sound from a middle-age healthy male subject, and to abnormal lung sounds acquired from a male patient with diffuse interstitial pneumonia. It is expected that the results of this research could be used to obtain a better signature of thoracic sounds for pattern recognition purpose, among other tasks.

1. Introduction

Thoracic sounds (TS) produced by the heart, the lung, stomach and muscles are important since they carry relevant physiological information regarding the function and medical condition of the physiological systems [1–4]. Consequently, a lot of efforts to analyze these sounds have been achieved to improve the understanding of the underlying physiological phenomena as well as their dynamical evolution. The TS

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Table 1 – Set of parameters used to compute different TFRs.

Time–frequency representations	Set of parameters	
SP	Window type	Rectangular, Hamming and Blackman-Harris
	Window length	9 linearly equidistant values in [N/10 – N/2]
WVD	–	–
CWD	Kernel parameter (σ)	27 linear equidistant values in $[1-\sigma_{\max}]$
SPR	Window type	Rectangular, Hamming and Blackman-Harris
	Window length	9 linearly equidistant values in [N/10 – N/2]
P_{BURG}	AR model order	[2–5]
	Window type	Hamming and Blackman-Harris
	Window length	9 linearly equidistant values in [N/10 – N/2]
P_{RLS}	TVAR model order	[2–5]
	Forgetting factor (λ)	9 linearly equidistant values in [0.75 – 1]
$P_{\text{RLS-VFF}}$	TVAR model order	[2–5]
	Expected noise variance (σ_e^2)	9 logarithmically equidistant values
P_{Kalman}	TVAR model order	[2–5]
	Measurement noise variance (σ^2)	Fixed at 0.1
	Process noise variance (q)	9 logarithmically equidistant values
SC	Mother wavelet	Complex Morlet
	Wavelet length	9 values along length of the signal
HHS	–	–

Note: N corresponds to the total number of samples of the signal under study.

have been characterized in the time and frequency domains to obtain features that can be used for classification and diseases stratification purposes. However, some aspects of the TS need to be considered, such as their non-stationary behavior and the multicomponent nature [2,4]. Nowadays, one of the tendencies to analyze TS is based on obtaining signatures in the time–frequency (TF) domain. Consequently, to add to the knowledge of the goodness of diverse time–frequency representations (TFRs) is important.

The spectrogram (SP) represents the classical analysis technique and it was applied in various research fields, such as the thoracic sounds [5]. However, other linear TFR has been proposed, such as the Cohen class of distributions with two very well-known members the Wigner–Ville distribution (WVD) and the Choi–Williams distribution (CWD) [6]. Also, estimation of linear TFR by the continuous wavelet transform named the scalogram (SC), time-invariant autoregressive modeling (Burg algorithm), time-variant autoregressive (TVAR) modeling by Recursive Least-Squares algorithm with fixed and variable forgetting factor (RLS and RLS-VFF) and by Kalman filter have emerged to overcome the disadvantages of the classical SP [7–9]. Furthermore, more recently the Hilbert–Huang spectrum based on the empirical mode decomposition of the signal has been taken as an alternative way to get the time–frequency information in a framework that does not need a kernel [10].

Heart sounds (HS) and lung sounds (LS) have been the focus of numerous research efforts since they provide valuable information in a noninvasive way of the heart mechanical activity and lung ventilation, respectively [11,12].

For HS, different TFRs have been used for analyzing normal sounds and those produced by prosthetic valves [13]; in spite of all the efforts there is no consensus about the suitable TFR for first heart sound (S1) [14]. The TFRs techniques have been analyzed in different ways, for instance Amit and Gavriely [14] used four TFRs and selected one by a clustering approach applied to the TFR's features extracted from S1 to classify the level of breathing resistance and pharmacological stress. In other studies the selection was performed just by qualitative observations on the TF information as the reported for the analysis of S2 [15]. Also, the selection of the best TFR has been done by the inclusion of mathematical models of the analyzed sounds according to the physiological phenomenon involved in their genesis; Chen and Durand [16] reported results following the former approach.

For LS the conventional spectrogram has been mainly applied to look for their time–frequency course [17–19]. In the case of continuous adventitious (abnormal) lung sounds known as wheezes, related mainly to the obstruction of airways, a mathematical model has been used to define their time–frequency course and it was validated using just the spectrogram [17,20]. Regarding discontinuous lung sounds known as fine and coarse crackles, that are related to the opening of abnormally closed airways, they also have been mathematically modeled but without the purpose to analyze them in the TF domain [21]. Lu et al. synthesized wheezes and normal breathing sounds at the tracheal level by including amplitude and frequency modulation features; however, just the spectrogram was used to assess the TF behavior of the simulated thoracic sounds [17].

The aim of the present study was to look for an omnibus technique to obtain the time–frequency representation (TFR) of thoracic sounds by assessing the performance of ten TFRs (see Table 1). The biological signals considered in this work were heart sounds (HS), normal tracheal sounds and