Respiratory sound analysis in healthy and pathological subjects:
A wavelet approach

Stefano Sello\textsuperscript{a,\ast}, Soo-kyung Strambi\textsuperscript{b}, Gennaro De Michele\textsuperscript{a}, Nicolino Ambrosino\textsuperscript{b}

\textsuperscript{a}Enel Research, Pisa, Italy
\textsuperscript{b}Pulmonary Unit, Cardio-Thoracic Department, University Hospital of Pisa, Italy

\textbf{1. Introduction}

Complex signals analysis is a crucial issue in many diagnostic fields and the information obtained is often the key to control unwanted critical phenomena. Combustion instabilities, for example, represent the major concern in industrial power generation systems, where modern lean premixed combustors are required to operate economically and reliably with low emissions over long periods with minimal shutdown time. Acoustic emissions provide a useful diagnostic signal to characterize and to predict complex transient flames because they are strictly linked to the temporal rate of heat release change. This topic deeply stimulated many efforts to develop and to apply different advanced acoustic signal analysis, obtaining very promising results [1,2]. The basic characteristics of these techniques suggest a wide application in signal analysis and in particular their use to complex biomedical signals appear very promising.

The total energy involved in the respiratory process comes from different sources: according to the Euler equation for a compressible fluid, we need to compare the internal work produced by muscular forces and the mechanical energy due to a ventilatory support, if any, with the sum of: (a) dissipative (frictional forces or resistive work); (b) elastic (airway compliance); (c) inertial (fluidodynamic forces); (d) acoustic (sound wave propagation). It is well known, as documented in the current wide literature, that the acoustic field gives significant information on the respiratory state, mainly due to its fluidodynamic origin, where the pressure fluctuations induced by airflow turbulence, strictly depend both on geometry and on physical properties of the involved airways [3].

Modern computer technology offers great advantages in terms of acquisition, storage and analysis of sounds that are normally heard through a stethoscope; this approach has provided new important insights into acoustic mechanisms and related quantitative diagnostics for respiratory diseases [4]. In particular, lung sound analysis to detect different kinds of flow obstruction, has drawn great attention recently because the respiratory acoustic measurements have shown to be very useful in the deep investigation of different upper airways pathologies [27]. The analysis of respiratory sounds allows us to reach a considerably more information of clinical utility than that obtained by a traditional auscultation and the new findings can only be interpreted in a complete acoustical framework.

Tracheal sounds recorded at the suprasternal notch are currently the topic of significant interest because the related
signal is strong with a wide range of frequencies and closely correlated to measured airflow. The main interest on the tracheal sound is due to its ability to indicate an upper airflow flow obstruction and also to give a source for more or less quantitative assessments of airflow. Further, the close correlation to airflow for tracheal sound, allow us to detect some peculiar features of the more weaker lung sound at frequencies below 300 Hz where most of the acoustic lung energy resides. On the other hand, an high frequency anomalous amplitude detected on the tracheal spectrum, is a clear indication of a pathological state for the whole respiratory system [4]. The generation of tracheal sound is mainly due to turbulent air flow in upper airways which causes pressure fluctuations and sound waves within the fluid. Because of the relatively short distance between the sensor and the different sources in the upper airways, tracheal sound is often considered the less filtered breath sound.

Tracheal sound have been characterized as broad spectrum noise covering a frequency range from near 100 Hz to more than 1500 Hz with a sharp drop in power above a frequency around 800 Hz. However, the spectral shape of tracheal sound is highly variable between various subjects and thus its parametric representation is more complex than that of other breath sounds. For this reason it is necessary to develop suitable mathematical and numerical methodologies in order to extract valuable information about respiratory health. Respiratory sounds are highly non-stationary pseudo-stochastic, or non-linear, signals due to variations of airflow rate and airflow volumes during respiration cycle. The non-linear character of the respiratory sound is mainly due to the complex turbulent flow dynamics and its structural interaction with the larger airway walls. For that reason wavelets provide a good method of decomposing these signals both in scale and time. During the last decade, they have been applied in different areas of mathematics, engineering, biology and medicine [5,6]. Because of their suitability for analyzing transient and non-stationary signals, they have become a powerful tool as an extension to the Fourier method, in different real applications mainly for helping in the recognition and detection of typical diagnostic features. Most biomedical signals are not stationary with highly complex time–frequency characteristics. Generally, they consist of short high-frequency components closely spaced in time, followed by long-term low-frequency components closely spaced in frequency. The wavelet method can provide both very good time resolution at high frequency and good scale resolution at low frequency. This property, together with the redundancy of information inherent in continuous wavelet signal representation, makes wavelets a powerful tool in medical research and diagnostic, like studies of precursors of heart disease [7–9], studies of brain response to evoked potentials, mainly for an early detection of Alzheimer’s disease [10,11], studies in human visual channels [12,13], investigations for singularity detection in pulmonary microvascular pressure transients [14] and analysis of surface electromyographic signals, for Parkinson’s disease analysis and diagnostics [15,16] and for respiratory sound analysis [17–21]. The main aim of the present work is to give a further contribution on how the wavelet methodology can be efficiently used to study and to characterize complex multiscale behavior of respiratory sound signals.

There is a need of non-invasive monitoring in respiratory physiology. Monitoring of respiratory parameters is essential in the treatment of acute and chronic respiratory diseases. In particular, evaluation of the work of breathing during spontaneous and assisted ventilation is an essential aspect of monitoring of effectiveness of mechanical ventilation. Rather interestingly, adequate monitoring is available in intubated mechanically ventilated patients but is rarely performed in non-intubated spontaneously breathing patients or in patients undergoing non-invasive mechanical ventilation (NIMV). Many tools for non-invasive assessment of respiratory activity have been proposed among the Respiratory Inductance Plethysmograph, Magnetometers, Optical Methods, Electromyography [22]. Unfortunately many of the measurements of breathing pattern and work of breathing in the acute patient are not accurate. Furthermore at the present there is no way to reliably and non-invasively monitor the work of breathing. At the present, many patients undergo non-invasive mechanical ventilation without an acceptable level of monitoring. Some ventilators have the facilities of monitoring tidal volume, pressures, flows, etc. However, such devices have currently no facility to monitor the degree of the respiratory muscle unloading, induced by non-invasive mechanical ventilation. One of the problems that currently limits a wide application of the non-invasive respiratory sound analysis is the technical difficulty of capturing a reliable signal from the surface of the body. Indeed no sensor is ideal and many technical problems related to a good sound capture remain to be solved.

In this work, we describe how a specific use of the wavelet analysis on broad-spectrum tracheal sound signals, it is able to distinguish between healthy subjects and patients with different respiratory diseases. More precisely, as a first step, we investigate here the ability of our wavelet-based method to quantitatively describe the respiratory state using a very synthetic vector index (the wavelet quartiles). In particular, the “normalization” effect of a non-invasive ventilatory support, on a given patient, can be now precisely quantified. Further work, also using the cluster analysis, will be devoted to see if and how this method can usefully distinguish between different respiratory pathologies. For this next step of our analysis we need a wider statistical sample of different patients, in order to point out specific features on the acoustic energy distribution in the related wavelet spectra.

2. Wavelet techniques

2.1. Fundamentals

Mathematical transformations are in general applied to raw signals to obtain important information that is not readily available from their time evolutions. The most common tool utilized in real-signal applications is the Fourier transformation which decomposes a given signal into its frequency components [23]. However, this technique requires that a signal to be examined is stationary, i.e. without time evolution of the frequency content. Actual biomedical signals are in general not stationary, with an intermittent and changing frequency pattern. The limitation of the Fourier analysis can be partly resolved by using a short-time Fourier transform, or Gabor transform, where we assume that the signal is quasi-stationary in a narrow time period. In this case we can apply the Fourier transform with a fixed time-evolving windows. On the other hand, the main advantage of the wavelets is the use of varying window size, being wide for low frequencies and narrow for the high ones, leading to an optimal time–frequency resolution in all the frequency ranges. Thus Fourier analysis is an adequate tool for detecting and quantifying constant periodic fluctuations in time series whereas, for intermittent and transient multiscale phenomena, the wavelet transform is more adequate to detect accurate time evolutions of the frequency distribution. For a more comprehensive and detailed description of the wavelet formalism, see Refs. [5,24,25].

The continuous wavelet transform represents an optimal localized decomposition of time series, x(t), as a function of both
time $t$ and frequency (scale) $a$, from a convolution integral [26]:

$$W_t(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^\prime \left( \frac{t - \tau}{a} \right) \, dt$$

(1)

where $\psi$ is called an analyzing wavelet if it verifies the following admissibility condition:

$$C_\psi = \int_0^{+\infty} |\psi(a\omega)|^2 \omega^{-1} \, d\omega < +\infty$$

(2)

where $C_\psi$ and $|\psi(\omega)|$ are the admissibility constant and the Fourier transform of the wavelet function, respectively.

In the definition, Eq. (1), $a$ and $\tau$ denote the dilation (scale factor) and translation (time shift parameter), respectively. We define the local wavelet spectrum:

$$P(k, t) = \frac{1}{2\pi k_0} \left| W_t \left( \frac{k_0}{k} \right) \right|^2, \quad k \geq 0$$

(3)

where $k_0$ denotes the peak frequency of the analyzing wavelet $\psi$. From the local wavelet spectrum we can derive a mean or global wavelet spectrum, $P(k)$:

$$P(k) = \int_{-\infty}^{+\infty} P(k, t) \, dt$$

(4)

which is related to the total energy $E$ of the signal $x(t)$ by

$$E = \int_0^{+\infty} P(k) \, dk$$

(5)

The relationship between the ordinary Fourier spectrum $P_F(\omega)$ and the global wavelet spectrum $P(k)$ is given by

$$P(k) = \frac{1}{C_\psi} \int_0^{+\infty} P_F(\omega) \left| \psi \left( \frac{k_0}{k} \omega \right) \right|^2 \, d\omega$$

(6)

indicating that the global wavelet spectrum is the average of the Fourier spectrum weighted by the square of the Fourier transform of the analyzing wavelet $\psi'$ shifted at frequency $k$ [25].

In this work we use the family of complex analyzing wavelets consisting of a plane wave modulated by a Gaussian (called Morlet wavelet):

$$\psi(\eta) = e^{i a \eta} e^{-\eta^2/2}$$

(7)

The selection of a particular analyzing wavelet is based upon what kind of information we are interested in extracting from the signal. Since the Morlet wavelet is complex, it can provide useful local information related to both amplitude and phase of transient signals, at a given scale $a$. In this study we chose to use the Morlet basis wavelet for its specific ability to furnish a complete information on the amplitude–phase relation over time. This property is especially important to select the significant wavelet power contributions during the time integration at a given scale. If we are mainly interested in the analysis of wavelet power spectra, then the choice of the analyzing wavelet is not very critical. Of course, in our respiratory sound application the continuous wavelet transform formulation is replaced by a discrete version when applied to a discrete sequence $x_n$ of data. As an example, Eq. (1) must be replaced by the following relation:

$$W_n(a) = \sum_{n=0}^{N-1} x_n \psi^\prime \left( \frac{n - n_0}{a} \right)$$

(8)

where $n$ is the localized time index.

2.2. Characterization of the wavelet power distribution: quartiles

A common way to characterize a frequency spectrum distribution is to divide it into parts, so that each part represents the same amount of energy. The fractions can be halves (medians), quarters (quartiles) or a different percentage of the total power spectrum [27]. The general percentile $i$ is determined by computing the frequency $f_i$, limiting the related part. The quartiles $f_{25\%}$, $f_{50\%}$, $f_{75\%}$, which divided the spectrum into four equals parts which have been proved particularly effective to characterize the power distribution. More precisely they give an evaluation of how the spectrum is balanced between low and high frequencies and thus can be used to characterize global changes in breath sounds [28].

The quartiles computation in the wavelet analysis framework is obtained starting from a proper version of the global wavelet spectrum as given by Eq. (4). More precisely, from the local wavelet spectrum we derive a time-averaged spectrum obtained by selecting only the significant power contributions, when compared to a background red-noise [24]. This selection process is only available if we know the time-resolved wavelet spectrum. In the following analysis, we assume that the computation of the global wavelet spectrum, (Eq.(6)), must be performed considering the above time-scale selection procedure.

Breath sounds may be abnormal in certain pathological conditions of the airways (e.g. bronchial obstruction) with anomalous high frequencies and intensity; for this reason the quartiles representation gives us an immediate and clear point of view of a given pathological state.

In order to obtain a synthetic information on the wavelet global power distribution, in this work we utilize a 3D space where the components of each vector are the above quartiles.

3. Experimental data

3.1. Subjects

The study was approved by the Ethical Committee of the University Hospital of Pisa and was performed according to Helsinki Convention. Informed consent was given by all subjects studied. The study was performed on 58 healthy non-smoker subjects (30 males, 28 females, age: 27–75 years) 44 smoker subjects (24 males, 20 females, age: 30–75 years) and in 24 patients (15 males, 9 females, age: 56–86 years) suffering from various respiratory diseases: 15 chronic obstructive pulmonary disease (COPD); 2 lung cancer; 5 restrictive thoracic and neuromuscular diseases; 2 obstructive sleep apnoea syndrome. All the patients were receiving drug treatment according to the

<table>
<thead>
<tr>
<th>Case</th>
<th>Disease</th>
<th>Age (years)</th>
<th>Smoker</th>
<th>$B_i$ (min$^{-1}$)</th>
<th>SB, NIMV (%), mmHg</th>
<th>$P_i$ O$_2$(mmHg)</th>
<th>$P_i$ CO$_2$ (mmHg)</th>
<th>$C_i$ (min$^{-1}$)</th>
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<tr>
<td>1</td>
<td>-</td>
<td>67</td>
<td>NO</td>
<td>20</td>
<td>-</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>COPD</td>
<td>70</td>
<td>EX</td>
<td>12</td>
<td>1 (SB)</td>
<td>63.7</td>
<td>58.5</td>
<td>80</td>
</tr>
<tr>
<td>3a</td>
<td>COPD</td>
<td>72</td>
<td>EX</td>
<td>24</td>
<td>2 (SB)</td>
<td>62.2</td>
<td>41.1</td>
<td>98</td>
</tr>
<tr>
<td>3b</td>
<td>COPD</td>
<td>72</td>
<td>EX</td>
<td>16</td>
<td>25 (NIMV)</td>
<td>64.5</td>
<td>62.1</td>
<td>90</td>
</tr>
</tbody>
</table>

$B_i$: breathing rate; SB: spontaneous breathing; NIMV: non-invasive mechanical ventilation, $C_i$: cardiac rate.
prescriptions of their primary care physicians. In particular, COPD patients were receiving regular treatment with inhaled bronchodilators. Diagnosis of COPD was according to ATS/ERS Standards [29]. All but two patients were on long-term oxygen. No patient was in long-term mechanical ventilation. Physiological characteristics of a sample of patients for COPD are shown in Table 1. Note that the main aim here is to point out the response of our method to a given generic pathological state as compared to a healthy case and the regularization effect of the non-invasive mechanical ventilation. The choice of showing the COPD conditions as a pathological example, it is motivated by their distinctive power distribution characteristics when compared to a healthy case.

3.2. Data acquisition

Two types of transducers are in common use for respiratory sound recording and research: small air-coupled electret microphones with a coupling chamber and contact accelerometers. However, the last ones are typically more expensive than electret microphones, are often fragile and may exhibit internal resonances near the sound frequencies of interest. For this reason here we used a proper microphone coupled to the skin by a closed chamber, similar to a stethoscope bell, with selected size and shape in order to capture the overall frequency range of interest. In particular, the bell-shaped air chamber follows the criterion of maximization of the amplitude of the microphone membrane motion with large contact areas and small internal volume. To verify this condition, we designed a bell-shaped air chamber with an external diameter of 35 mm and a distance skin-microphone of 15 mm [27]. The tracheal sound recording has been performed locating an air-coupled electret condenser microphone at the suprasternal notch using a hand-held method, i.e. without an external mechanical support. This experimental set-up allow us to better check the sensitivity of the acoustic signal to different positions and applied pressure. In particular, we developed a real-time algorithm in order to check the correct applied pressure of the microphone and to normalize the quality of the recorded amplitude signal. In a future stage of the system development, we plan to use a proper collar-based device in order to better standardize, independently from the operator, the recorded signal quality. The microphone sensitivity is: $-62 \pm 3 \, \text{dB}$ and the reliable frequency range is: $20$–$16,000 \, \text{Hz}$ (universal direction condenser microphone by Melchioni Electronics, cod. 492821188) (Fig. 1).

The acquisition sampling rate was $8000 \, \text{Hz}$ with a 16-bits digitization amplitude resolution. The typical frequency range analyzed was 148–2000 Hz where a finite impulse response (FIR) band-pass filter with 149 linear coefficients was used. The frequency response of the microphone is nearly flat in the range: $80$–$5000 \, \text{Hz}$, allowing a reliable acoustic recording in the range examined. The sources of the quality degradation, in the non-invasive acquisition of the respiratory sound signals, are very common and various; for this reason we needed a quality selection procedure before starting the analysis. In this work we used a real-time moving low-pass filter of the raw acoustic signal to extract the correct amplitude of the very low-frequency breath cycle: in particular we assumed that a sufficiently good signal must have a significant amplitude whose numerical value was empirically established on a statistical basis. As example of results given by the above procedure, Figs. 2 and 3 show a typical bad and good sound

**Fig. 1.** Spontaneous respiratory sound analysis procedure and functional scheme.

**Fig. 2.** Quality selection procedure: bad signal ($\text{FFT peak value} = 7.09 \times 10^{-9}$).
signals, respectively. In fact, only in Fig. 3 we can correctly extract the breath cycle frequency as shown in the Fourier analysis. For the sound analysis of a given subject we typically recorded five tracks with elapsed time of 20 s, i.e. we repeated five recordings lasting 20 s each. Then we performed the wavelet analysis and the related statistical computation as explained in the previous section [31]. All the developed software has been implemented in NI LabView environment. The overall analysis, system and software package, is covered by an European patent [32].

3.3. Measurements and monitoring

Dynamic lung volumes were measured by mass flow sensors (Vmax229, SensorMedics, Yorba Linda, USA) with the patients in the seated position according to standard procedure Official Statement of the European Respiratory Society [33]. The predicted values of Quanjer [34] were used.

Before, during and after sound recordings respiratory and heart rate and arterial blood pressure were monitored. Subjective

Fig. 3. Quality selection procedure: good signal (FFT peak value = $1.40 \times 10^{-5}$).

Fig. 4. Wavelet analysis for a typical control subject (see case #1 in Table 1). The original respiratory signal (expressed in V) is shown in the upper panel; the wavelet spectrum with time displayed in the horizontal axis and scale (frequency) displayed in a log scale in the vertical axis is shown in the central panel. The related scale expressed in Hz is also shown.
sensation of dyspnoea was assessed by means of a modified Borg Scale [35].

3.4. Study protocol

Sound recordings were performed in sitting position, at rest, during spontaneous breathing (healthy subjects and patients) and during non-invasive mechanical ventilation (only in patients). Patients were adapted to NIMV in a short session (1 h) on the day of study. A commercial nasal mask of adequate size for each patients nose was used (Softseries or Gold seal masks, Respironics Inc., Murrysville, PA, USA). For each patient Pressure Support Ventilation was delivered by means of the same portable ventilator able to compensate for leaks (BiPAP(r) Vision, Respironics Inc., Murrysville, PA, USA). The ventilator circuit was equipped with a non-rebreathing valve (Respironics Inc., Murrysville, PA, USA). The level of inspiratory pressure support (IPS) was increased slowly by 2 cm H2O increments starting from 2 cm H2O, until the patients indicated that breathing was uncomfortable. Hence, that level of IPS was decreased by 2 cm H2O, and the resultant level was applied during the study.

4. Results of the wavelet mean power distribution

A wavelet map of sound signal recorded in a healthy subject is shown in Fig. 4. In the upper panel of the figure we show the original breath signal as recorded by the experimental device described in the previous section, expressed in its natural units. In the central panel there is the wavelet map of the power content using an arbitrary color contour scale. The horizontal axis displays

Fig. 5. The global wavelet spectrum in log-log scale for the control subject of Fig. 4. Quartiles: $f_{25\%} = 250.2$, $f_{50\%} = 361.3$, $f_{75\%} = 518.7$.

Fig. 6. Wavelet analysis for a COPD patient (see case #2 in Table 1). The original respiratory signal (expressed in V) is shown in the upper panel; the wavelet spectrum with time displayed in the horizontal axis and scale (frequency) displayed in a log scale in the vertical axis is shown in the central panel. The related scale expressed in Hz is also shown.

Fig. 7. The global wavelet spectrum in log-log scale for the patient of Fig. 6. Quartiles: $f_{25\%} = 453.9$, $f_{50\%} = 861.3$, $f_{75\%} = 1222.3$. 
the temporal variable expressed in seconds and the vertical shows the frequency values in a logarithmic scale. Note from the map the difference between inhale and exhale phases: the first one is characterized by an average greater power intensity with respect to the second one. Each breath cycle is separated by a longer absence of signal. However, our analysis is performed on the whole recording time interval, irrespective of the inhale/exhale phases. The frequency range selected was between 148 Hz and 2000 Hz because, as said, this interval contains all the significant energy components. As we can see at a first qualitative inspection of the global wavelet spectrum, for the control subject the power shape is as expected, i.e. a broad spectrum noise with a sharp drop above a cut-off frequency of approximately 600 Hz. This feature, typical for our set of tested healthy subjects during normal breathing condition, is in agreement with results shown by Charbonneau et al. [30] using a similar air bell cavity with an electrect condenser microphone (cut-off frequency about 400 Hz). However, other authors indicate a different cut-off frequency for healthy subjects, between 800 Hz and 1600 Hz, but using a contact type sensor [4,27].

Continuous wavelet transform contains redundant information at all scales and, in general, it is not useful to consider all the details contained in the wavelet scalograms. Here we are mainly interested in extracting information which can be useful for a general classification of subjects in term of the disease level and its time evolution. Another important requirement is the relative simplicity of the whole procedure in order to allow easy implementation in a biomedical context. For that reason it was...
more convenient to perform a statistical analysis on the set of wavelet maps, mainly through integral quantities derivable from the wavelet results. In particular, as said, the ability of wavelet analysis to resolve time events, allow us to select consistent and significant time intervals used to compute integral quantities, such as the global wavelet spectrum. This selection is based on a statistical comparison between a given local power contribution and an assumed background spectrum. Here we consider a lag-1 autoregressive Markov process related to a red-noise spectrum [24]. The most efficient parameter found to describe the sound energy distribution, in terms of statistical reliability, is the quartile representation based on the mean global wavelet spectrum obtained from the set of the different acquisitions for a given subject. The Fig. 5 shows the mean global wavelet spectrum, for the case shown in Fig. 4. Figs. 6 and 7 show the results of the same analysis performed on a patient affected by a severe respiratory insufficiency, COPD. The mean global wavelet spectrum, as we know from the literature, clearly displays an increment of the power in the intermediate high-frequency range, due to related ineffective dissipation mechanism of the acoustic energy.

Fig. 10. The global wavelet spectrum in log–log scale for the patient in Fig. 8 before ventilation. Quartiles: $f_{25\%} = 444.7$, $f_{50\%} = 796.5$, $f_{75\%} = 1213.1$.

Fig. 11. The global wavelet spectrum in log–log scale for the patient in Fig. 9 during ventilation. Quartiles: $f_{25\%} = 278.6$, $f_{50\%} = 444.7$, $f_{75\%} = 768.7$.

Fig. 12. The 3D representation of quartiles for a sample of different selected subjects described in Table 1. Note the normalization effect in a COPD patient due to a non-invasive ventilatory support. $F1$, $F2$, $F3$ on the axes indicate the quartiles: $f_{25\%}$, $f_{50\%}$, $f_{75\%}$. 

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In order to point out the normalization effect of the forced ventilation procedure, in Figs. 8–11 we show the results of the analysis on a selected patient affected by COPD before and during ventilation. In particular, Fig. 8 displays the wavelet map and Fig. 10 displays the anomalous mean global wavelet spectrum during spontaneous breath; while Figs. 9 and 11 show the same information, where the effect of the ventilation is, as expected, a regularization of the spectrum shape.

In Fig. 12 we show a 3D plot for the graphical representation of the quartiles related to the previous mean global spectra: in particular, as reference point, we included the position of a typical control subject. The pathological condition and the normalization effect of the ventilatory support are, at the same time, clearly evidenced.

In general, we found that the effect of the ventilation is the regularization of the spectrum shape, independently from the kind of the respiratory disease. Fig. 13 displays the whole set of tested subjects, without considering the kind of pathology examined, in order to better show the coarse location of clusters obtained in the quartiles 3D space. Table 2 shows the mean quartiles values and their standard deviations computed for homogeneous classes of subjects. It is interesting to note that the computed clusters tend to assume a non-isotropic shape with only few preferred spatial directions. However, further work is needed to clarify if this property is a real characteristic or otherwise it depends to a limited number of cases in our statistical sample. Moreover, the ability to distinguish between different pathologies clearly needs more subjects and a wider statistics, which it would be the main task of a future work. However, these preliminary results confirm that a proper wavelet mean power distribution method, applied to respiratory sound signals, can be able to adequately distinguish at a quantitative level a generic pathological state from regular breath conditions. In principle, through the same wavelet technique it appears possible to follow with reliability the time evolution of the disease level of a given patient on the basis of related shape variation of the mean power distribution.

5. Conclusions

The present method of tracheal sound analysis seems very promising. More precisely, the proposed wavelet analysis on broad-spectrum tracheal sound might be useful in a quantitative

![Fig. 13. The 3D representation of quartiles for the whole sample (N = 126) of analyzed subjects. Blue: healthy non-smoker subjects; yellow: smoker subjects; red: patients. Note that the symbol size is related to its 3D space origin distance. F1, F2, F3 on the axes indicate the quartiles: f_{25\%}, f_{50\%}, f_{75\%}.](image)

<table>
<thead>
<tr>
<th>Class</th>
<th>$&lt;f_1&gt;$</th>
<th>$&lt;f_2&gt;$</th>
<th>$&lt;f_3&gt;$</th>
<th>$\sigma_1$</th>
<th>$\sigma_2$</th>
<th>$\sigma_3$</th>
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<td>58</td>
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<tr>
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<td>No-COPD patient</td>
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<td>238.37</td>
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</tbody>
</table>

Table 2: Wavelet quartile mean values and standard deviations for homogeneous classes of tested subjects.
evaluation of the severity stage of different respiratory diseases and their treatment. In particular, it might be used as a non-invasive tool to better evaluate one of the main effects of mechanical ventilation, namely the unloading of respiratory muscles [36].

The respiratory sound analysis, based on the wavelet technique, properly combined with a statistical power distribution method, resulted quite coherent with the expectations derived from the clinical evaluation. Furthermore this method appears more effective than the standard breathing pattern data which quantifies the main functional activities of patients. In particular, we confirmed that the non-invasive energetic analysis of the respiratory sound is useful in order to discriminate the respiratory state of normal and subjects and patients with respiratory diseases. Moreover our approach, based on mean wavelet energy power distribution, allows a clear and effective graphical representation through the related quartiles. The mean energy content and its distribution, detected in the statistical results from the wavelet analysis, reflect the expected qualitative picture of respiratory failure of patients with respect to healthy subjects. The important feature of the above wavelet analysis performed on complex biomedical signals, is the necessity to develop a careful statistical analysis on an extended set of results, in order to extract the essential information, e.g. for classification and diagnostic purposes. The use of the wavelet-based method, instead of more classical signal analyses, such as standard Fourier method, for this specific respiratory signals, is justified by the intrinsic unsteady and non-linear feature of the raw data. More precisely, through the wavelet analysis it was possible to establish the correct power distribution of the signal by means of a time-selective procedure of the wavelet map. This is a crucial aspect of our quantitative procedure based on the wavelet quartiles information. Of course, for very distinctive signals such as a control vs. COPD patient, the energy distributions of the wavelet and Fourier-like spectra can result quite similar; however, the wavelet information is more effective and less dependent from time localized artifacts located at significative scales, always present in the respiratory signal data. This feature allow us to obtain more clear and sensitive results, when based on the wavelet mean power distribution, irrespective of the distinctive character of different respiratory signals. Due to the significant clinical state variability for different subjects and the intrinsic noise contamination induced by the experimental test, it is of great importance to accurately select the raw acoustic data in terms of their quality, i.e. the signal-to-noise ratio. However, it is important to stress that the results of the present analysis are quite preliminary, mainly due to a little representative statistical sample of subjects with few different respiratory pathologies. To this respect we need also a precise characterization of patients and their respiratory sound responses. A recent work by Banner et al. [37], shows that the power of breathing (POB), determined non-invasively with the use of an artificial neural network, may be a clinically useful tool to better control the patient's dependency on ventilatory support, if combined to breathing pattern parameters. Our preliminary results in patients undergoing mechanical ventilation indicate that the "pathological pattern" of sound signal may be at least partially reversed by this therapeutic tool. This preliminary observation suggests the possibility to use these non-invasive signals to monitor the effectiveness of a therapeutic tool. For this purpose further experimental studies must be performed. In this context, it would be of great interest to explore the possibility of correlating our acoustic power distribution information, through the quartiles analysis, with the POB. In fact, in this way it is possible to join different approaches and their important information: the first one based on the properties of acoustic wave propagation and the second one based on the total mechanical work of the respiratory muscles. A more comprehensive and detailed work covering all the specific biomedical and acoustic aspects implied in the present study is in progress.

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