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Extraction of Diaphragmatic EMG Using DWT

¹ IBISC CNRS FRE 2873, Université d'Evry, 91020 Evry Cedex, France

² LIS-INPG UMR 5053, 46 avenue Félix Viallet, 38031 Grenoble, France

³ Unité de Réanimation du service de Pneumologie, 47-83, boulevard de l'Hôpital, 75651 Paris Cedex 13, France

⁴ Equipe MATISSE-SAMOS CES CNRS-UMR 8173, Université Paris 1, Paris cedex 13, France

E-mail: {vincent.vigneron,Elmostafa.fadaili}@ibisc.univ-
evry.fr,{similowski,christian.straus}@psl.aphp.fr,
christian.jutten@lis.inpg.fr

Abstract. Analysis of respiratory muscle activity by means of oesophageal electrodes is a promising technique to detect and diagnose neuromuscular pathology. The diaphragm electromyogram (dEMG) is a mixture of signals generated by different active muscles due to the phenomena related to respiratory volume. Wavelet transform can be used as a preprocessing tool to denoise dEMG signals from artefact and ECG. In the present study, we have established the effectiveness of this tool to extract dEMG from a set of experimental recording.

Keywords: diaphragmatic EMG, esophageal electrodes, wavelet transform, denoising

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1. Introduction

At the heart of signal processing lies the task of extracting specific information from a set of recorded signals, for instance the occurrence of certain patterns, periodic ranges, discontinuities, irregularities, etc. The wavelet transform (WT) can contribute to the answer to these questions whenever the expected phenomena has a multiscale structure. Typical examples of such patterns are jumps, puff, artefacts, edges or locally varying orders of differentiability. On the contrary, the localization of discontinuities with the help of the classic Fourier transform (FT) is seldom possible. The standard method for the investigation of irregularities in the diaphragm is the analysis of the esophageal EMG recording. A typical dEMG signal consists of inspiratory and expiratory segments with an alternation at about 10 cycles/min as illustrated in Fig. 1. Hence, dEMG signals can be assigned to the class of weakly stationary signals.

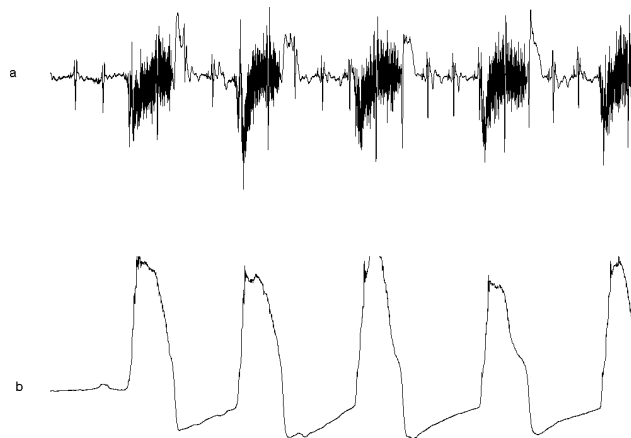


Figure 1. a) Diaphragmatic EMG signal. b) corresponding respiratory volume (respiratory cycle consists of an inspiration and an expiration).

The EMG signals are usually corrupted by cardiac activity reflected in electrocardiographic (ECG) and cardiac pulse (CP) signals. Also, artefacts like variation of electrode contact impedance produced by electrode movement during effort test contaminate EMG recording. The reduction of these interferences is necessary in order to calculate parameters related directly to the respiratory muscle activity so that reliable results and conclusions are obtained. Acquisition and processing of dEMG signals are well established techniques (Roeleveld, Stegeman, Vingerhoets

& Van Oosterrom 1997, Khalil, Duchêne, Marque & Leman 1997). Nevertheless, dEMG signal is generated by different respiratory muscles signals that overlap in time and frequency domain that result in a complex interference pattern of difficult interpretation. Thus classical filtering approaches cannot guarantee an effective extraction of dEMG signals. Graphic demonstration shows that ECG artifact is apparent throughout (Fig.1); however, methods for eliminating ECG artifact are available with appropriate integrators and waveform gating, if desired, see *e.g.*(Mananas, Romero, Topor, Bruce, Houtz & Caminal 2001, Deng, Wolf, Schnell & Appel 2000). Since their introduction, it has been noticed that wavelet transform can be used for removing noise from signals (Donoho 1995). The principle consist to decompose noisy mixture into an orthogonal wavelet basis, to suppress the wavelet coefficients smaller than some threshold, and reconstruct denoised signal by inverse transform.

We propose here to use wavelet decomposition as a preprocessing tool to extract dEMG activity from esophageal signals. We will show how this decomposition can eliminate artefact and ECG from experimental recording.

This paper is organized as follows: section 2 describes how the wavelet transform can be used in dEMG processing, section 3 presents a method for inspiratory puff start and endpoints detection based on use some statistical tools. Section 4 presents the details of our data acquisition and experimental protocol and theirs corresponding results. Finally, section 5 presents some future work of this study.

2. Wavelet decomposition

The proposed approach is based on the use of wavelets transform (WT) and theirs properties. We briefly recall here some important points related to our utilization. More details about wavelets transform can be found in (Daubechies 1992, Mallat 1989).

One of the major disadvantage of the Fourier transform lies in its lack of localization: the Fourier transform considers phenomena in an infinite interval, and this is far from our everyday point of view. It decomposes a signal in trigonometric functions which oscillate infinitely with teh same period, and these have no local character. The wavelet transform (WT) allows more flexibility: the *wavelet*, which can be any chosen function, can be *shifted* and *dilated* to analyse signal s . If the so-called wavelet ψ is dilated by a factor a and translated to a point b , then the wavelet family is defined by

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right). \quad (1)$$

The signal s is examined by the wavelet transform by forming the scalar product of s with translated and dilated versions of ψ . The continuous wavelet transform (CWT) of signal $s(t)$ is a time-scale representation defined as

$$W_s(a, b) = \int_{-\infty}^{+\infty} \psi_{a,b}(t)s^*(t)dt, \quad (2)$$

where $a \in \mathbf{R}^+$, $b \in \mathbf{R}$ and $*$ denotes the conjugaison operator. For discrete values $a = 2^i$, $b = i2^j$ and when $\Psi_{i,j}(t)$ form an orthogonal basis of wavelets, signal $s(t)$ can be write as :

$$s(t) = \sum_{i,j} D_s^{i,j} \Psi_{i,j}(t). \quad (3)$$

where $D_s^{i,j} = W_s(2^i, i2^j)$ is called the *discret wavelet transform* (DWT).

Wavelet transform has numerous applications in signal processing like noise cancelation. One of the major contribution of wavelets denoising (Donoho 1995) was called “soft thresholding” introduce the following operator for selection of coefficients $D_s^{i,j}$:

$$x_{sth} = \begin{cases} x - \text{sgn}(x)\lambda & \text{if } |x| \geq |\lambda| \\ 0 & \text{else} \end{cases}$$

Then, denoised signal $s_d(t)$ using this thresholding procedure is

$$s_d(t) = \sum_{i,j} (D_s^{i,j})_{sth} \Psi_{i,j}(t)$$

The choice of threshold value can be determined in many ways. For example, when noise perturbation is supposed white Gaussian process, the value of threshold is $\lambda = \sigma \sqrt{2 \log_2 N}$ where N is the length of noisy signal.

In practice, the coefficients $D_s^{i,j}$ are calculated using fast wavelet decomposition and reconstruction algorithm proposed in (Mallat 1989). It is, in fact, a classical scheme in the signal processing community, known as the 2-band wavelet system described by the finite response response (FIR) filter w and which is called the *scaling filter*.

We will discuss here about how the wavelet transform can be used in EMG processing. In fact, because non-stationarity of EMG signals, Fourier analysis seems to be poor for describing transient event like brief muscle contraction, due to their limitation in temporal resolution. Some advantages of using wavelet transform for EMG analysis are showed in (Laterza & Olmo 1997) and several approaches based on WT were proposed for EMG signals processing. In (Kumar, Pah & Bradeley 2003) for instance, EMG has been decomposed using different families of wavelets for determining muscle fatigue and in (Hu & Wang 2004) is proposed method based on WT to extract MUAP's from surface EMG signals.

Regarding the mother wavelets, several ones were proposed for EMG analysis and their choice is conditioned by the nature of the information to extract from raw signal. Morlet wavelets for example is one of the most used for analysis of the surface EMG signals. In order to understand the influence of the choice of mother wavelets, let us consider first the example of dEMG signal in figure 1 and consider three mother wavelets for analysis: *Mexican hat*, *Gaussian*, *Daubechies*. Figure 2 shows the absolute value of CWT for different wavelets. For the same signal and scale level,

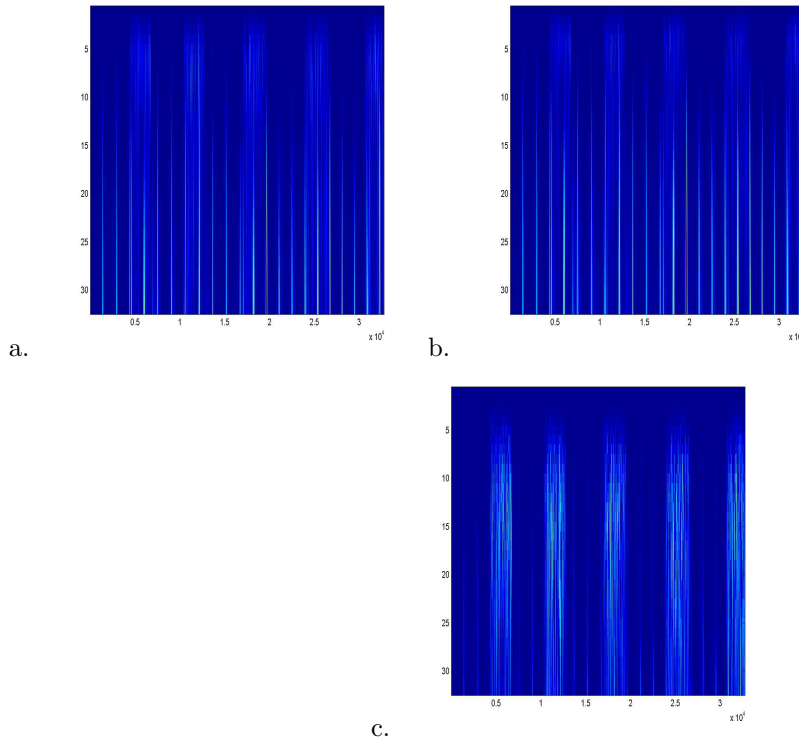


Figure 2. Absolute value of CWT of dEMG for three mother wavelets a. Gaussian (second derivative), b. Mexican hat, c. Daubechies.

the three images exhibit some different details. The first and second ones shows the peaks who corresponds to ECG signal who is not desired for our processing. The third image exhibits more

energy corresponding to dEMG component than the one corresponding to ECG. Consequently, we can choose this wavelet for extracting dEMG. In (Flanders 2002) is showed some details of some resemblance between Daubechies family of wavelet and MUAPs. Notice that we can use other wavelets like symlets, coiflets,... who belong all to family of the *orthogonal and compactly supported wavelets*(Daubechies 1993).

In Figure 3.a is plotted the denoised signal by soft thresholding procedure described previously using Daubechies wavelets and in Figure 3.b it's corresponding CWT.

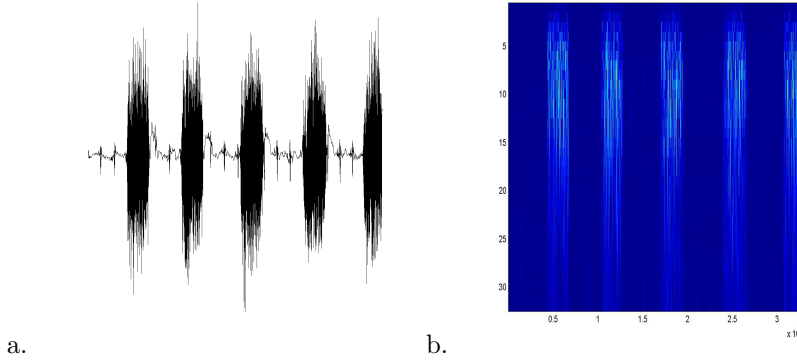


Figure 3. a. Denoised dEMG using Daubechies wavelets. b. corresponding CWT

3. Inspiratory puff start and endpoints detection

The accurate detection of the inspiratory or expiratory puff start and endpoints (PSED) means that subsequent processing of the data can be kept to a minimum. This problem can be referred to as the endpoint location problem (Lavielle & Teyssi re 2006).

The method proposed in (Lavielle & Teyssi re 2006) and used in this article is a global approach: all the change-points are simultaneously detected. These change points are estimated by optimizing some penalised contrast (Lavielle 2005) $J(\tau, x) + \beta pen(\tau)$ where $J(\tau, x)$ measures how the model obtained with the change-point sequence τ fits the signal x and its role is to locate the change-points as accurately as possible. The authors propose to define $J(\tau, x)$ from the logarithm of Gaussian likelihood (even if x is not Gaussian) to detect changes in the mean and/or the variance of x . The term $pen(\tau)$ depend only on the dimension of the model and the parameter β ajust de the trade-off between the minimisation of $J(\tau, x)$ and $pen(\tau)$.

We will describe here briefly the principle of the proposed algorithm. Let us consider a sequence $x(t)$ of one dimensional process and consider change in the variance an mean of x . More precisely, we assume that there exists an integer K , a sequence $\tau = \{\tau_0, \tau_1, \dots, \tau_K\}$ with $\tau_0 = 0 < \tau_1 < \dots < \tau_K = n$ and :

$$E(x(t)) = \mu_k, E((x(t) - E(x(t)))^2) = \sigma_k^2, \forall \tau_{k-1} + 1 \leq t \leq \tau_k \quad (4)$$

with $(\mu_k, \sigma_k) \neq (\mu_{k+1}, \sigma_{k+1})$.

The proposed contrast function for the detection of changes in the mean and/or variance of x is :

$$J(\tau, x) = \frac{1}{n} \sum_{k=1}^K n_k \log(\sigma_k^2) \quad (5)$$

About the choice of β , the authors suggest to use $\beta = \frac{4 \log n}{n^{1-v}}$, where $v \in (0, 1)$ is some scaling parameter of the process x and can be estimated from observed data.

For penalty function, in (Birge, Lucien, Massart & Pascal 2007) is proposed an example of optimal function. Finally, the change-points τ are detected by

$$\tau = \arg \min(J(\tau, x) + \beta pen(\tau)) \quad (6)$$

using some recursive method. Notice that the authors propose also an automatic procedure for estimating the number of segment K . More details can be found on (Lavielle & Teyssière 2006). Let us now apply this procedure to the example of dEMG signals of figure 4.a. The result of change-points detection procedure applied to denoised dEMG is showed in figure 4.b, where the inspiratory puff start and endpoints are clearly distinguished. More results and discussion will be presented in the following sections.

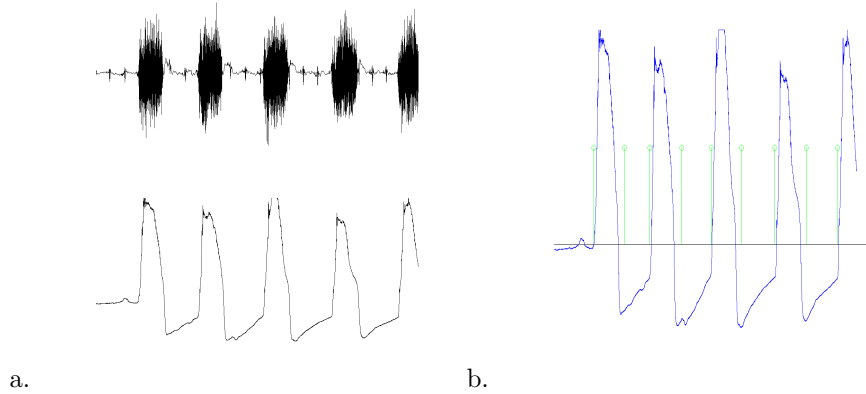


Figure 4. a. Denoised dEMG using Daubechies wavelet. b. point-change detected from denoised signal compared to the respiratory volume.

4. Assessment on real dEMG data

4.1. Materials

Subjects Six healthy volunteers participated in this study. During the experiment, subjects were sitting on a chair equipped with headrests, abdomen unbound or lying, and breathed through a nose mask connected to a low resistance respiratory nonrebreathing valve. The inspiratory port of the nonrebreathing valve was connected to the external source of a negative pressure.

Data acquisition dEMG recordings were obtained by using three esophageal electrodes (see Fig. 5). All signals were fed to a Nihon Kohden electromyograph. The myographic signals were amplified and bandpass filtered using a multichannel analog amplifier. Bandpass filtering is employed, with a high-pass filter to remove the signal's direct current component and a low-pass filter set below the data acquisition frequency to avoid distortion (by aliasing) of the signal caused by undersampling (Supinski, Fitting & Bellemare 2002). Filter settings could vary, depending on the type of electrodes and the posture. The selected bandwidth and the sampling frequency were respectively 5-600 and 2000 Hz, and the gain was set to 5 000 or 10 000 for these signals. EMG and one flow signals were simultaneously recorded.

4.2. Experimental protocole

The experimental protocole consisted of breathing with an inspiratory threshold load (ITL) and/or with an expiratory resistive load (ERL). Various postures were used, as detailed in Tab. 1. The muscle groups were recorded also under forced sniffs or abdominal pushed conditions. Cardiac activity with a periodicity of approximately 0.9 seconds, is observed in these signals. Myographic signals, corresponding to a several respiratory cycles recorded, are visualized in Fig. 6.a.

4.3. Result

Using Daubechies' scaling filters w of size $N = 56$ for DWT decomposition with level $L=15$, the denoised dEMG signals in posture P4 of one selected patient are plotted in figure 6.b for three

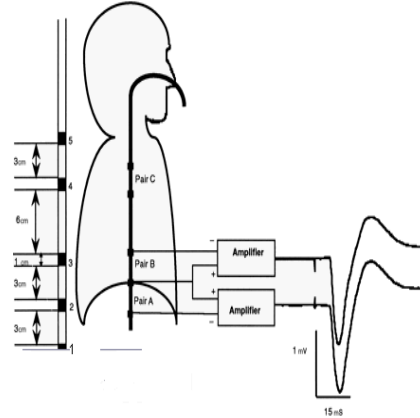


Figure 5. Oesophageal site of the three electrodes pairs A, B, C.

n^o	posture
P1	calm breathing, sitting
P2	hyper-ventilated breathing without load, sitting
P3	sniffs, no control of muscle groups, sitting
P4	ITL† and ERL†, sitting, polypnea
P5	sniffs with diaphragme predominance
P5bis	calm breathing, lying

Table 1. Characteristics of the various postures we studied.

† ITL=*inspiratory threshold load*.

† ERL=*expiratory resistive load*.

recordings, where the inspiratory puffs are clearly extracted. In order to show the effectiveness of detecting start and end of inspiratory cycle, we have plotting in figure 7 the result of the comparison with ventilatory volume. Some light shift can be verified in start of inspiratory puff due to the beginning of inspiratory effort (MUAP's recruitment) before air flow starting. For end-point inspiratory puff, the existence of post-inspiratory activities can explain the shift with air flow end point. In Table 2 are presented the quality of proposed denoising method using signal to noise ratio in dB : $SNR = 20 \log \left(\frac{\sigma_{ispi}^2}{\sigma_{exp}^2} \right)$, where σ_{ispi}^2 and σ_{exp}^2 are respectively the variances of denoised dEMG in inspiratory and expiratory cycles. We can verify that their are some postures more interesting for denoising quality, P5 for example.

Finalty, in figure 8 are plotted the power spectral densities of patient 1 in posture P4 for three channels before and after denoising. The difference in spectral domain between the two signals is due to the noise cancellation (hight frequency) and attenuation of electrocardiogram component.

5. Conclusion & future work

In this study, we showed the performance of a discret wavelet transform in the extraction and analysis of esophageal dEMG recordings. The method presented here is effective in artefact denoising and ECG attenuation. The obtained results shows that start and end point of inspiratory puffs can be determined with high precision using some statistical approach based on contrast optimisation.

Our future interest is to use wavelet transform for extraction of dEMG from surface electrodes. The recorded signals from surface electrodes seems to be more affected by noise and artefact than esophageal ones. We can also use others signal processing sophisticated techniques like blind

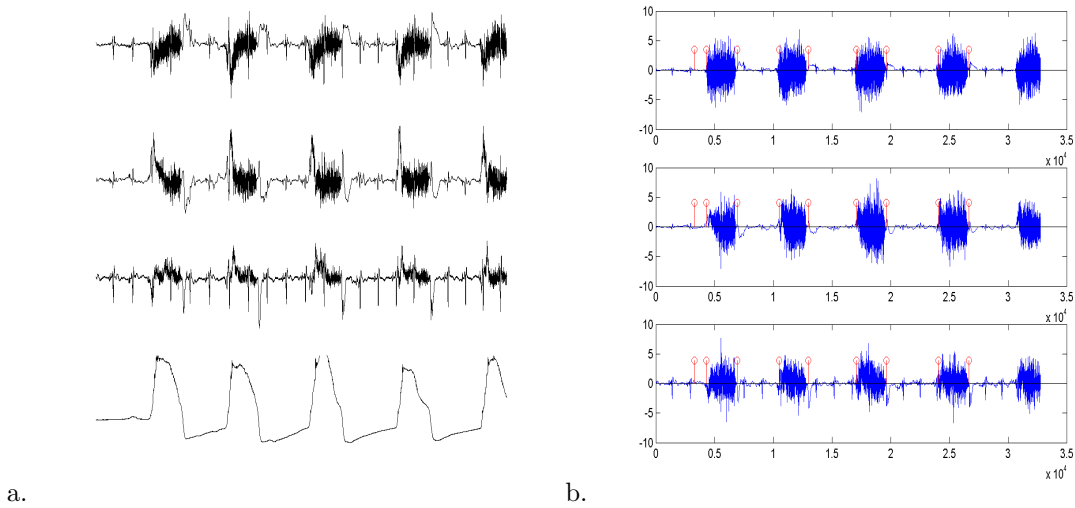


Figure 6. a. Three raw dEMG recordings and respiratory volume (bottom) in posture 4. b. denoised signals and air flow zeros.

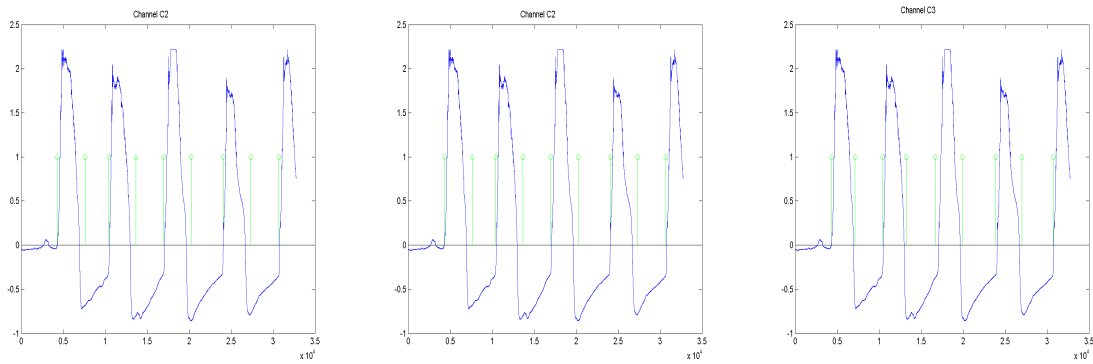


Figure 7. Comparison of detected puffs start and end points to respiratory volume for three channels C1, C2, C3.

sources separation which emerged recently in biomedical signal processing as strength tool to isolate different complements from multi-channel recordings.

For application of dEMG extraction, we can be interested to inspiratory puff form in order to characterize the so calling *respiratory profile* that can help the clinician logically approach a respiratory pathology.

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Patient	Canal / Posture	P1	P2	P3	P4	P5	P5bis
1	C1	5.6582	0.7906	7.8078	10.4805	9.8252	3.6464
	C2	12.0161	0.6638	8.2400	16.3099	11.0720	7.0237
	C3	2.8049	3.8645	4.1126	6.9503	7.5136	3.9190
2	C1	2.8398	12.9992	15.6433	12.0922	12.4847	7.2287
	C2	2.7975	10.6754	7.5327	6.6752	11.2684	2.4461
	C3	2.0099	6.0811	6.9258	9.5021	6.6600	0.7310
3	C1	1.1829	3.5709	4.0622	4.5978	-	1.9479
	C2	0.7215	2.1583	2.0734	1.0936	-	-0.4262
	C3	1.3388	2.5390	2.8566	0.2349	-	1.7105
4	C1	4.5223	2.8561	12.0354	10.3418	7.6313	2.5349
	C2	2.3932	-0.1585	7.9342	0.7201	6.1571	-0.1470
	C3	3.5819	-1.7862	8.2500	-2.4182	3.1050	1.0966
5	C1	-6.9004	1.2306	0.5496	-2.1225	2.3561	1.3020
	C2	-5.7245	3.6963	1.7321	-1.4237	3.3337	0.9663
	C3	-5.6218	11.1899	2.9796	10.3322	16.5555	1.3575
6	C1	-0.2308	0.9467	2.1021	5.3028	7.1963	-
	C2	0.6070	-0.6205	2.1758	4.5684	6.8204	-
	C3	0.0863	0.3034	3.5695	1.4065	7.9153	-

Table 2. Signal to noise ratio SNR(dB) for different patients, 6 postures and three channels.

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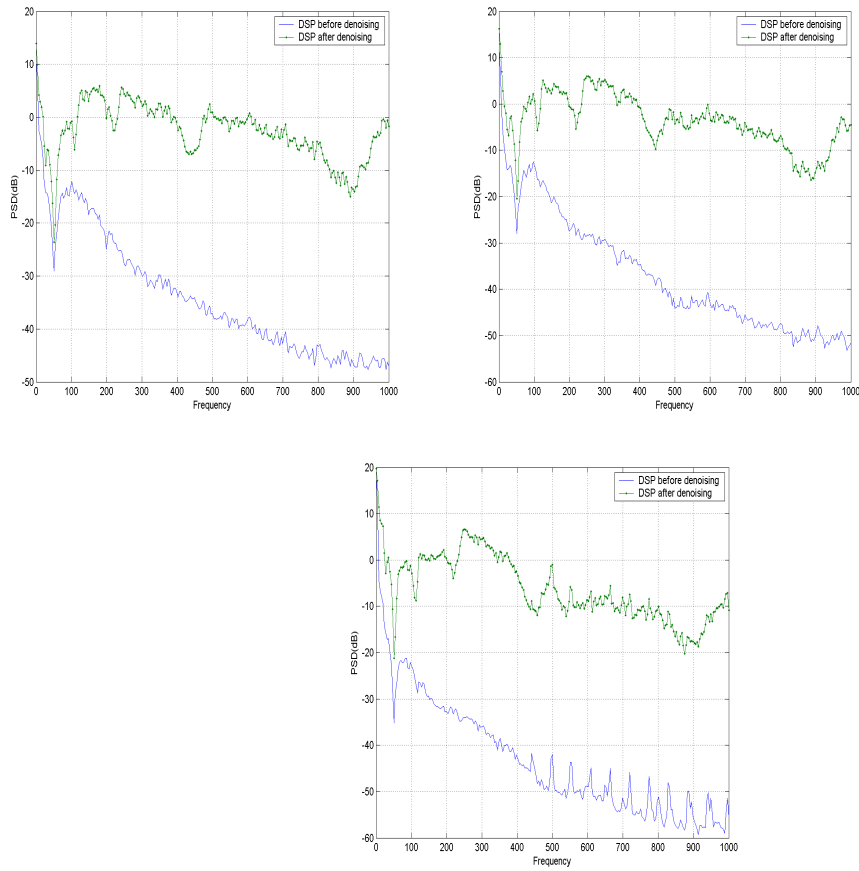


Figure 8. PSD of dEMG signals before and after wavelets denoising for 3 channels .