International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:2, 2008

Noise Removal from Surface Respiratory EMG Signal

Slim Yacoub, Kosai Raoof

Abstract**—**The aim of this study was to remove the two principal noises which disturb the surface electromyography signal (Diaphragm). These signals are the electrocardiogram ECG artefact and the power line interference artefact. The algorithm proposed focuses on a new Lean Mean Square (LMS) Widrow adaptive structure. These structures require a reference signal that is correlated with the noise contaminating the signal. The noise references are then extracted : first with a noise reference mathematically constructed using two different cosine functions; 50Hz (the fundamental) function and 150Hz (the first harmonic) function for the power line interference and second with a matching pursuit technique combined to an LMS structure for the ECG artefact estimation. The two removal procedures are attained without the use of supplementary electrodes. These techniques of filtering are validated on real records of surface diaphragm electromyography signal. The performance of the proposed methods was compared with already conducted research results.

Keywords**—**Surface EMG, Adaptive, Matching Pursuit, Power line interference.

I. Introduction

THE electromyography via the surface was the easiest method for the EMG respiratory acquisition. Concerning simplicity of the electrode devising and its non-invasive characteristic, this technique is very interesting especially in the case of long-time monitoring. However the signal to noise ratio was really very bad. As a result, the signal analysis became very difficult particularly in case of weak electromyographic activities. The two principal artifacts that disturb EMG of diaphragm were ECG artifact [1,2,3] and the electromagnetic interference 50 and 150 hz [4]. Fig.1 shows a signal of the disturbed diaphragm mainly by the ECG and the power line interference 50Hz and 150 Hz. The ECG artifact of the heart beating lied in the same area of EMG frequency moreover the variable amplitude ratio between them caused by the non-stationary EMG signal nature made the ECG, very difficult to eliminate [6,7]. The second artifact that contaminates the EMG signal concerned the power line interference.

This noise arises from the environmental electric sources such as: the turning machines and the electric power. Thus the human body behaved like an antenna which caught electromagnetic interference signals.

In order to reduce the effect of this disturbance, first of all, we tried to realize a good preparation of the body skin indeed the skin is abraded and cleaned with abrasive cream and alcohol. Second to reduce the effect of the cable length the signals are differentially amplified [4, 8, 9] twice. However, this preliminary filtering remained insufficient in case of a deep contaminated surrounding and weak muscular activities.

Made up of these, the use of analogical or digital filters of fixed band centered on 50 Hz and on 150 Hz for the electromagnetic component and on [20-40Hz] for the ECG signal (maximum energy of ECG) seems to be essential here. Although these filters allowed the reduction of the noises they also eliminate some useful signal components. To preserve useful signals, we suggested the filtering of these disturbing artefacts by using the LMS adaptive algorithm [11, 12] but without introducing supplementary electrodes to the noise reference in order to minimize the presence of electronics.

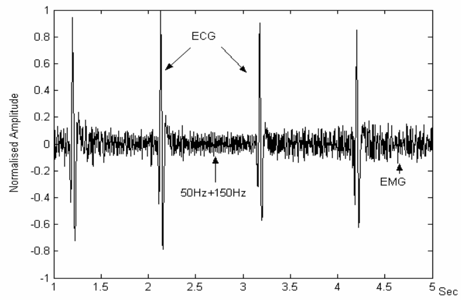

Fig. 1 Raw surface respiratory EMG signal contaminated with ECG and power line interference signals

II. Experimental configuration

In our case study, we chose an experimental configuration with electrodes placed between the seventh and eighth intercostals space in order to be more sensitive to diaphragm. We selected an inter-electrode distance of 36 millimeters and metallic electrodes of 3 millimeters diameter. This exactly specific location has been chosen in order to particularly pay attention to diaphragmatic EMG in his costal part. The electrodes are carefully positioned and situated on clean skin disinfected with alcohol and with abrasive paste [13].

The signal amplification was realized via two levels: The first level amplifies by using the instrumentation amplifier (INA101). As soon as the second level amplifies (LF442), it filters frequency band [10-230Hz]. Then, it digitizes at 1024

Slim Yacoub is with Physics and Instrumentation Department of the Institut National des Sciences Appliquées et de Technologies de Tunis (e-mail: slimyacoub@yahoo.fr.

Kosai Raoof is with Laboratoire des images et des signaux (LIS) a l'Institut National Polytechnique de Grenoble - INPG – Université Joseph Fourier - Grenoble I France. (kosai.raoof@lis.inpg.fr)

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:2, No:2, 2008

Hz sampling frequency (one channel 12 bits ADC and are processed by digital signal processor Analogue device ADC 2105).

III. Performance Indicators

To compare different methods of power line interference filtering, the Total Power in percent (TP%) is calculated according to:

$$TP_s\% = \frac{\sum_{i=f_1}^{f_2} \left(P_s(i)\right)^2}{\sum_{i=f_1}^{f_2} \left(P_r(i)\right)^2}.100 \quad (1)$$

Ps (i) and *Pr (i)* are respectively the spectral densities amplitudes of the processed signal and the raw EMG signal contaminated with obvious ECG artefacts and power line interference artefacts PLI per frequency bins and f_i are frequency bins.

To evaluate the effect of the processed methods on the PLI and respiratory EMG signal separately we use the EMG specific segments ($TP_{EMG}\%$) free of PLI and PLI specific segments ($TP_{PLI}\%$) free of EMG .

However, to quantitatively asses the validity and efficiency of the proposed ECG removal technique we used in this study the most common estimator of amplitude features: the Average Rectified Value (ARV).

The average rectified value of signals is defined in percent with regard to:

$$ARV_S\% = \frac{\sum_{k=1}^{N} |s(k)|}{\sum_{k=1}^{N} |r(k)|}.100 \quad (2)$$

N represents the number of samples, s (k) the processed signal samples and r (k) the raw respiratory EMG signal contaminated with obvious ECG artefacts.

To evaluate the effect of the processed methods on the ECG and EMG signals separately, we use the segments of the EMG signal between two consecutive ECG spikes ($ARV_{EMG}\%$) free of ECG and the segments of consecutive ECG spikes ($ARV_{ECG}\%$) free of EMG signal [27].

IV. Power Line Interference Filtering

The electromagnetic components 50Hz and 150 Hz were signals localized on the frequency-band of EMG signal. In order to eliminate them, different techniques of digital filtering were possible. The classical filtering methods using a moving average window [14,15] or a band rejector [16] filtered simultaneously both the electromagnetic noise and the useful EMG components. So they were not really adaptable to our case study. However Barata proposes in [17], estimates the amplitude and phase of the power line interference signal from a clean EMG recording segment. This method will fail if the amplitude and phase change during the EMG recording session. Other techniques used the adaptable filters type LMS (Least Mean Square) which were suggested in [11,18 and 19]. These techniques might give interesting results especially according to ECG recording signal case. To be optimal these techniques require a reference input signal that is correlated with the interferences signal. Then the reference input is adaptively filtered and subtracted from the original noisy signal. Widrow suggests a reference input constructed with a fixed delay Δ inserted in the reference input drawn directly from the primary input. The delay chosen must have a sufficient length to cause the respiratory EMG signal components in the reference input and to become decorrelated from those in the primary input. The evaluation of the autocorrelation function of a respiratory EMG signal shows that the delay must have a sufficient length 150 milliseconds [22]. To enhance the signal to noise ratio (SNR) Bahoura proposes in [19] the same LMS structure but estimates the reference noise signal with a band-pass filter centered on the electromagnetic interference. However, it was not really sufficient because there was always the presence of the useful signal EMG with electromagnetic components.

A. The suggested Methods

The two methods for respiratory EMG estimation in this investigation require an estimation of power line interference PLI as a reference signal $P\hat{L}I_{ref}$ so that an LMS adaptive filter can be used to cancel PLI in the contaminated EMG signal.

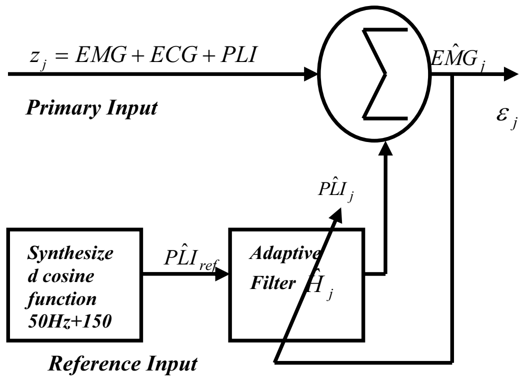

Fig. 2 The (A_F) structure of adaptive power line interference filtering : $z_j = EMG + ECG + PLI$, raw signal; EMG, signal of interest ; PLI , noise; $P\hat{L}I_{ref}$, reference noise ; $P\hat{L}I$, estimate of the noise with the adaptive filter; $\hat{H}_j$,adaptive filter coefficient ; $E\hat{M}G$, filtered signal

The process initially generates an input reference $P\hat{L}I_{ref} = cos(w_{50}t) + cos(w_{150}t)$ to the adaptive filter made of a pure cosine functions mathematically constructed; 50Hz (the fundamental) function and 150Hz (the first harmonic) function. as shown in Fig.2.

This reference input is correlated, in some unknown way, with the noise (*PLI* signal) of the primary input z_j . Then, the reference input is adaptively filtered $P\hat{L}I$ and subtracted from the primary input to obtain the $E\hat{M}G$ estimated signal ε_j , the filter is optimal by minimizing the least mean square error (equation 3) [11,12].

The coefficients $\underline{\hat{H}}_j$ of the adaptive filter are computed according to equation (4).

The error ε_j represents the difference between the original signal $EMG + ECG + PLI$ and the adaptive filter output $P\hat{L}I$.

The fundamental equations of this algorithm are:

$$\varepsilon_j = Z_j - \underline{\hat{H}}_j^T \underline{X}_j^T \tag{3}$$

Where $\underline{X}_j$ is the adapted signal ($P\hat{L}I$) and $\underline{\hat{H}}_j$ is the adaptive filter coefficients.

$$\underline{\hat{H}}_{j+1} = \underline{\hat{H}}_j + 2.\mu.\varepsilon_j.\underline{\hat{X}}_j \tag{4}$$

Z_j is the original signal ($Z_j = EMG + ECG + PLI$), ε_j is the estimated EMG signal with LMS algorithm and μ is the Rate of convergence and accuracy of the adaptation process.

$$\underline{\hat{H}}_j^T = \left[\hat{H}_1, \hat{H}_2, ...\hat{H}_M\right] \tag{5}$$

The finite impulse response of the adaptive filter $\underline{\hat{H}}_j$ is carried out with M coefficients.

A cautious choice may be to make M sufficiently long compensating the phase shift that could exist between the synthesized $P\hat{L}I_{ref}$ signal and the PLI of the raw respiratory EMG signal.

A sufficient length of an LMS filter using the adaptive filter structure can be formulated in the following expression:

$$N > f_s/f_{pli}. \tag{6}$$

f_s is the sampling frequency and f_{pli} is the lowest interference frequency

The difference between the first two methods used here involved the reference estimation procedure. Specially, the first method estimate the reference by using synthesized cosine functions while the second method use for the extraction of the reference a band pass filter varying from 49.5 to 50.5 Hz and from 149.5 to 150.5 Hz.

B. Results

To prove the efficiency of our technique (A_F) reducing effectively the power line interference signal, we compare below the results of our method with the results obtained with Bahoura (B_F) adaptive filter applied to the EMG case. Algorithms will be tested on real respiratory EMG signals.

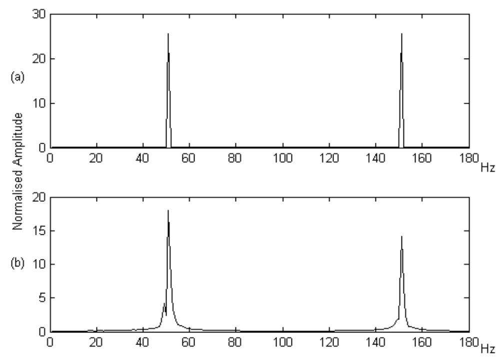

Fig. 3 Power spectral densities of: (a) Reference extracted with 50 Hz and 150 Hz synthesized periodic signals with cosine functions (A_F) method. (b) Reference noise signal extracted from the original signal with a band-pass filter with frequency varying from 49.5 to 50.5 Hz and from149.5 to 150.5 Hz (B_F) method

Fig. 3 a shows the spectral density of the noise power line reference 50Hz and 150 Hz synthesized by cosines function (A_F method). Noise reference signal extracted with pass-band filter [49-5Hz-50.5Hz] and [149.5Hz-150.5Hz] (B_F method) is shown on Fig.3b. Compared to (A_F) method (B_F) method yet showed some useful EMG spectral components around 50 Hz and 150 Hz frequency which confirmed the insufficiency of this method to provide a clean reference input signal.

Respiratory EMG signal contaminated by ECG signal and power line interference signal is shown in Fig. 4a. Fig. 4b and. Fig. 4c represents respectively the estimation of power line

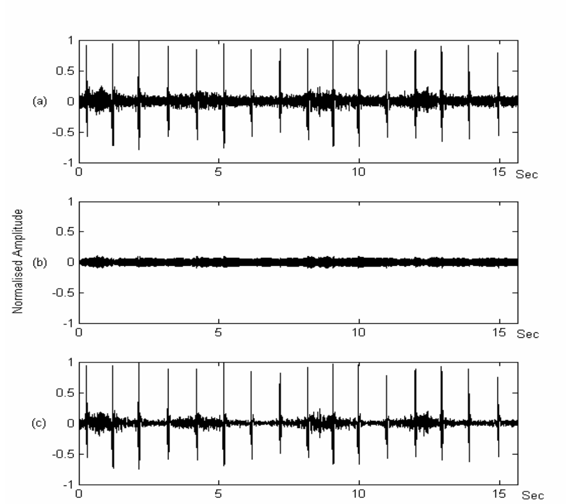

Fig. 4 Power line interference artifact removal with A_F method: (a) Raw surface respiratory EMG signal contaminated with ECG and power line interference signals; (b) Power line interference estimation; (c) Respiratory EMG signal after power line interference subtracting

Interference signal $P\hat{L}I$ and respiratory EMG signal $E\hat{M}G$ applying the already designed method A_F. Using this proposed method we can note substantial cancellation of the PLI artefact as shown on Figure 4.

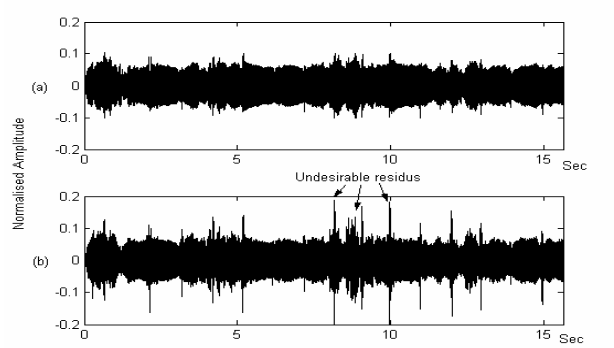

Fig. 5 Power line interference estimation using various methods: (a) A_F: The new adaptive method. (b) B_F: Bahoura adaptive method

In order to prove the efficiency of the suggested method compared to the one designed in [19], we presented in Fig.5a and 5b the LMS adaptive filter output. When the adaptive filter reference is respectively carried out by generating cosines function (A_F) method and applying band-pass filters ([49.5 - 50.5 Hz] and [149.5 -150.5 Hz]) (B_F) method. On the contrary we show in Figure 6 the spectral densities of these signals. Indeed Fig.6a shows the spectral density of respiratory EMG signal contaminated by ECG signal and power line interference signal and in Fig.6b and 6c we present respectively the spectral density of the LMS adaptive filter output with the new (A_F) method and the (B_F) method. It's clear from this Figure that the (A_F) method (Fig.6b) reduces considerably the undesirable EMG spectral components around 50Hz and 150 Hz frequency compared to the case of (B_F) method as shown on Fig.6c.

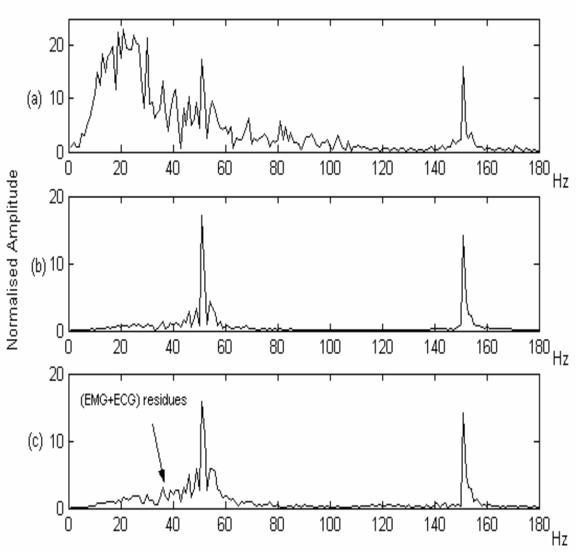

Fig. 6 Power spectral densities of: (a) raw respiratory EMG signal contaminated with ECG and Power line interference signal. (b) Power line interference estimation using (A_F) method. (c) Power line interference estimation using (B_F) method

To quantify the effects of the proposed methods on the PLI and the EMG spectral content separately, we evaluate the TP of the 50Hz and 150Hz (PLI), over the 49 to 51 Hz range for the 50 Hz and over the 149 and 151 Hz range for the 150Hz. table1 depicts the Total power mean (TP%) of PLI cleaned signal relative to the PLI contained in the raw signal in percentage, evaluated with the two segments described above. However, The Total Power mean (TP%) of the cleaned respiratory EMG signal, relative to the raw respiratory EMG signal in percentage, is calculated to avoid PLI over the 1 to 45 Hz range, the 55 to 145 Hz range and the 155 to 250 Hz range. We present as well in table1 the Total power (TP%) mean of respiratory EMG cleaned signal relative to the raw respiratory EMG signal in percentage, evaluated with the segments before mentioned. It's clear that the (A_F) method preserves more than 95% of spectral power of EMG features while this method suppresses more than 94% electromagnetic interference PLI spectral power. However, we note for (B_F) methods more than 24% of power alteration in EMG.

TABLE I TOTAL POWER (TP%) OF A 50 AND 150 HZ POWER LINE INTERFERENCE EXTRACTED FROM A CONTAMINATED RESPIRATORY EMG SIGNAL RELATIVE TO A PURE SIMULATED 50 AND 150 HZ INTERFERENCE (PLI) IN PERCENT, TP MEAN IS EVALUATED WITH THREE SEGMENTS: 1-45HZ, 55-145HZ AND 155 -250HZ, FOR EMG AND WITH TWO SEGMENTS 49 TO 51 HZ RANGE FOR THE 50 HZ AND OVER THE 149 AND 151 HZ RANGE FOR THE 150HZ.FOR PLI B_F : BAHOURA ADAPTIVE FILTER; A_F : THE NEW PROPOSED METHOD

TP (%)			
		Method	
	SNR level(db) EMG/PLI	**B_F**	**A_F**
PLI evaluation	5	90	94.5
EMG evaluation	5	76	95

V. ELECTROCARDIOGRAM ARTIFACT FILTERING

The EMG respiratory surface signal is contaminated too by the ECG Electrocardiogram artefact and it has been always the objective of several studies. In fact, some of them suggested a high-pass cut off frequency to estimate the spectral component of the EMG [10], because ECG signal overlaps in frequency domain with the surface respiratory EMG this method will results in a signal information loss. Other methods consisted in choosing temporary windows [20] in which the electrocardiogram ECG signal didn't exist. This method fails in case of highly electrocardiogram rhythm. The use of adaptive algorithms type LMS [3,11,12] requires an additional channel to record the ECG signal for use as a reference input for the noise canceller. In order to avoid these supplementary electrodes a Widrow adaptable structure, was suggested by [21] where the input reference is carried out using band pass filter ([20-40Hz]. This method was not really efficient because the existence of EMG residual in the reference signal, causing the distortion of the original EMG signal.

A. The adaptive suggested filtering method

To improve the adaptive filter reference input of [21] we have already suggested an adaptive technique in the precedent studies in which the noise-reference is estimated by a pass-band filter fixed rather on the QRS complex [22]. The obtained results showed a logic amelioration of the EMG/ECG signal to noise ratio. We suggest in this article a method that allows us to obtain a highly qualified noise reference. In this new technique we demonstrate how two steps will be combined as shown in Figure 7: The first step uses a widrow adaptive filter type LMS and a noise reference

$\hat{ECG}_{ref}$ extracted by pass-band filtering [10-15Hz], this step aims to filter the $\hat{ECG}$ signal. Whereas to filter the ECG signals again, in order to get a new input noise reference $\hat{ECG}_{mp\_ref}$ the second step applies firstly the matching pursuit algorithm [23,24,25]. Secondly we apply once again the LMS adaptive structure to filter the $\hat{ECG}_{mp}$ signal.

We choose the Matching Pursuit algorithm for his high resolution and local ability to adapt to transients structures. It is an iterative, non-linear procedure. The MP decomposes signal into the summation of a series of linear expansion function. The waveforms ("atoms") are selected from a redundant dictionary $D = \{g_\lambda\}_{\lambda \varepsilon \Gamma}$ of vectors of a unit module.

The algorithm of vector pursuit begins by choosing the waveform $g_{\lambda 0}$ that matches the signal *f,* as described in equation (9), and at each consecutive steps, the whole dictionary is searched and an atom $g_{\lambda n}$ that is adapted ($< R^n f, g_{\lambda n} >$ is largest) to the particular segment of the signal (residuum $R^n f$, left after subtracting results of previous iterations.) is picked up.

$$f = \langle f, g_{\lambda 0} \rangle g_{\lambda 0} + R^1 f$$
(8)
$$f = \sum_{n=0}^{M-1} < R^n f, g_{\lambda n} > g_{\lambda n} + R^M f$$
(9)

The number of iteration depends on the decomposed signal length; it is fixed after test applied on real situation. The first term $\sum_{n=0}^{M-1} < R^n f, g_{\lambda n} > g_{\lambda n}$ of equation (9) represent the second step electrocardiogram ECG reference signal estimation $\hat{ECG}_{mp\_ref}$.

The algorithm is performed on MatLab using Wave Lab toolbox. For a decomposed signal of N=16384 samples. The number of iteration of the matching pursuit procedure is fixed to 70, to ovoid EMG signal estimation. The FIR filter coefficients are fixed to 32 >1024/50.

We select Symmlet wavelet family for their similarity to the ECG signal [26], especially eight order (Symmlet 8) as mother wavelet.

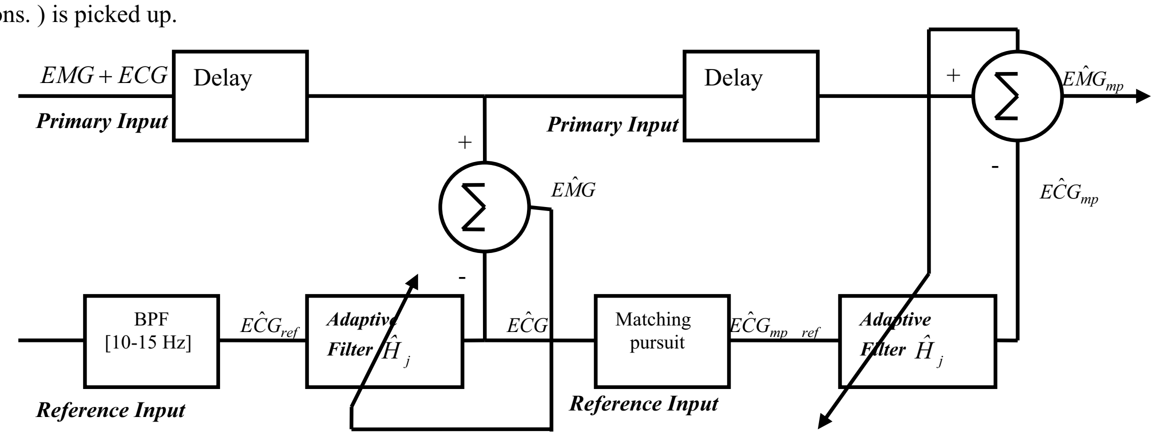

Fig. 7 The ECG noise canceller algorithm (AMP): $z_j = EMG + ECG$, raw signal; EMG, signal of interest ; ECG, noise; $\hat{ECG}_{ref}$, reference noise ; $\hat{ECG}$, estimate of the noise with the adaptive filter; $\hat{H}_j$,adaptive filter coefficient ; $\hat{EMG}$, filtered signal at the first step. $\hat{ECG}_{mp\_ref}$, estimate of the reference noise with the matching pursuit; $\hat{ECG}_{mp}$, estimate of the noise with the adaptive filter; $\hat{EMG}_{mp}$, filtered signal at the second step.

B. Results

The adaptive process needs initially an input reference. We present in Figure 8 references noise signal estimation of the ECG.

Fig. 8a presents the case of an ECG noise reference obtained by the decomposition of the signal with the matching pursuit algorithm (AMP method) however, Fig. 8b presents the case of an ECG reference estimated with a pass band filter ($BPF_{10\text{-}15hz}$) fixed on the ECG-QRS component [10-15Hz] it's obvious that according to this Figure that the best reference noise signal estimation ECG_{ref} it's for the new AMP method in fact according to the ARV% we obtain more than 85% of ECG signal estimation with scarcely any EMG residue on the contrary with the $BPF_{10\text{-}15hz}$ method we obtain only 60% of ECG signal estimation with more than 4% of EMG residue (table2).

Filtering results of respiratory surface EMG is shown on Figure 9. The Fig. 9b and 9c show the LMS adaptive filter outputs. When the adaptive filter reference is respectively carried out by the AMP method and by applying band-pass filters ([10-15 Hz]) ($BPF_{10\text{-}15hz}$). It is important to notice the undesirable residual ECG signal contained in the EMG signal estimation with $BPF_{10\text{-}15hz}$ method as shown in Fig. 9c.

We notice too that the frequency components of the EMG signal (less than 20Hz) are better preserved as shown on the Figure 10 with AMP method. This may be explained by the fact that the LMS filter adapt to EMG component that could exist in the reference signal when the $BPF_{10\text{-}15hz}$ method is applied.

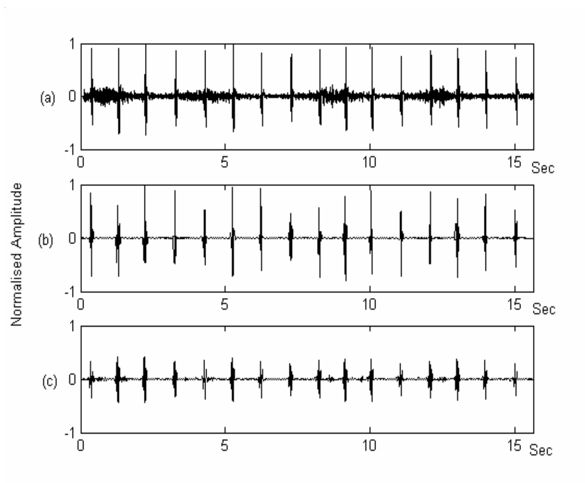

Fig. 8 ECG noise references signals extracted with different methods:
(a): Raw respiratory EMG signal contaminated with ECG signal.
(b): Using matching pursuit (AMP) method.
(c): Using Band Pass Filter BPF [10-15Hz] ($BPF_{10\text{-}15hz}$) method.

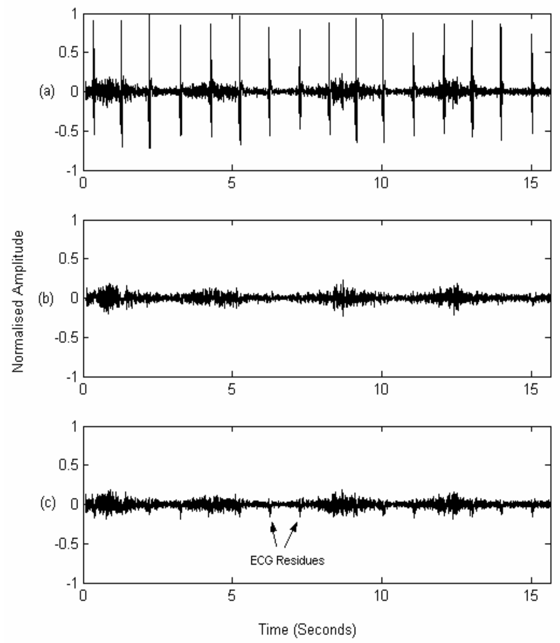

Fig. 9 Reduction of the ECG artefacts
(a): Raw respiratory EMG signal contaminated with ECG signal.
(b): Cleaned EMG signal with (AMP) method.
(c): Cleaned EMG signal with ($BPF_{10\text{-}15hz}$) method.

In order to better confront the two methods we evaluate separately for each method, the effect of filtering on both EMG respiratory signal and ECG signal estimation (table 3). The results evaluated show that the ARV% of EMG is more than 99% when we have applied AMP method. On the contrary, we loose accounting for the ARV%, more than 10% of signal EMG amplitude by applying ($BPF_{10\text{-}15hz}$) method. The two methods applied estimate more than 90% of ECG signal amplitude (ARV%), but in reality, AMP method has got the highest value which is equal to 97.8%.

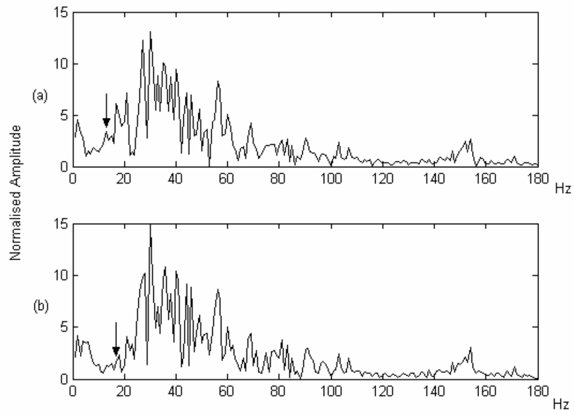

Fig.10 Power spectral density estimation of cleaned respiratory EMG signal with.
(a): New AMP method.
(b): $BPF_{10\text{-}15hz}$ method.

To conclude, it is showed in Figure 11 the two phases of surface EMG signal filtering. The first phase consists in filtering the electromagnetic components 50 and 150Hz (Fig.11b) then, in the second phase we filter the ECG signal by applying the AMP method (Fig.11c). The obtained results showed clearly the improvement of the signal to noise EMG/PLI and EMG/ECG in both cases.

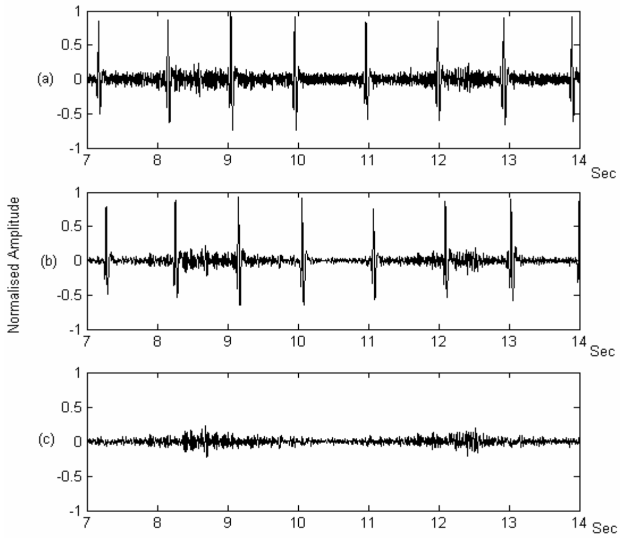

Fig. 11 (a) Raw surface respiratory EMG signal contaminated with ECG and power line interference signals; (b) Power line interference removal after applying (A_F) algorithm; (c) ECG signal removal after applying (AMP) algorithm.

TABLE II COMPARISON OF ECG REFERENCE SIGNALS AND EMG RESIDUAL SIGNAL AMPLITUDE EXTRACTED WITH AMP AND B_F METHODS USING, THE AVERAGE RECTIFIED VALUE (ARV) MEAN

ARV Amplitude (%)		
	Method	
Raw EMG	**$EMG_{10\text{-}15hz}$**	**EMG_{AMP}**
100	4	0
Raw ECG	**$ECG_{10\text{-}15hz}$**	**ECG_{AMP}**
100	60	85

TABLEIII COMPARISON OF ECG SIGNALS AMPLITUDE ESTIMATION AND EMG SIGNALS AMPLITUDE ESTIMATION EXTRACTED WITH AMP AND B_F METHODS USING, THE AVERAGE RECTIFIED VALUE (ARV) MEAN

ARV Amplitude (%)		
	Method	
Raw EMG	**$EMG_{10\text{-}15hz}$**	**EMG_{AMP}**
100	90	99
Raw ECG	**$ECG_{10\text{-}15hz}$**	**ECG_{AMP}**
100	91	97.8

I. CONCLUSION

The surface respiratory EMG signal has a bad signal to noise ratio. The principal noises that disturb such signals are the power line interferences and ECG artefact of the heart beatings. This work explored, considered new techniques of noise filtering. In case of electromagnetic interference it is shown that the use of synthesized reference noise with the help of cosines function allows us to obtain satisfying results. Concerning the filtering of electrocardiogram ECG component it's carried out in two steps. The first one aims at getting the finest ECG noise reference signal estimation by combining two structures: an LMS structure in which the reference is performed with a band pass filter [10-15Hz] followed by a matching pursuit algorithm. In order to cancel the ECG signal the second step applied the LMS structure again with the reference obtained at the first step. The effectiveness of the method for noises reduction was shown by analysis attenuation of the energy of the noise and the preservation of the signal energy. In addition this new structures (A_F and AMP) seems to be robust to an increase of noise whereas concerning the power line interference (PLI) signal the reference noise is mathematically constructed with cosine function then does not depend on the quantities of PLI contained in the signal. As for the ECG filtering the two combined stages with a good choice of mother wavelet and the matching pursuit algorithm permit us a high ability to extract ECG signal without EMG regardless with an increase of signal to noise favourable to EMG. The proposed procedure may also be applied without the use of supplementary electrode pairs, which will have interesting implications on future usage with fewer cables in mechanics.

REFERENCES

[1] Deng.Y, Wolf W, Schnell R, Appel U. New aspects to event-synchronous cancellation of ECG interference: an application of the method in diaphragmatic EMG signals. IEEE Trans Biomed Eng. 2000; 47(9):1177-1184.

[2] Sinderby. C, Lindström. L, Grassino. A.E. Automatic assessment of electromyogram quality. Automatic EMG analysis. Journal of Applied Physiology. 1995; (79): 1803-1815.

[3] Marque C, Bisch C, Dantas R, Elayoubi S, Brosse V, Perot C. Adaptive filtering for ECG rejection from surface EMG recordings. Journal of electromyography and kinesiology 2005; (15):310-315.

[4] Levkov C, Mihov G, Ivanov R, Dascalov I, Christov I, Dotsinsky I. Removal of power-line interference from the ECG: a review of the subtraction procedure. Biomedical Engineering Online 2005, 4:50 doi:10.1186/1475-925X-4-50.

[5] Gideon.F, Inbar & Antoine.E Noujaim . On surface EMG spectral characterization and its application to diagnostic classification. IEEE Transactions on Biomedical Engineering, 1984; 31(9):597-604.

[6] Hualou Liang, Zhiyue Lin, Fuliang Yin. Removal of ECG contamination from Non linear Analysis 2005; (63): 745-753.

[7] Drake J D M, Callaghan J P. Elimination of electromyogram contamination from electromyogram signals: An evaluation of currently used removal techniques. Journal of electromyography and kinesiology 2006; (16):175-187.

[8] Huhta J C, Wbester J G. 60 Hz interference in electrocardiography. IEEE Trans Biomed Eng. 1973; 20:91-100.

[9] Metting Van Rijn, Peper A, Grimbergen CA. High-quality recordings of bioelectrical events, Part 1: Interference reduction, theory and practice." Med Biol Eng Comput. 1990; 28:389-397.

[10] Redfern. M.S, Hughes.R.E, Chaffin. D.B. High-Pass filtering to remove electrocardiographic interference from torso EMG recordings. J Clin Biomech 1993; (8) : 44-48.

[11] Widrow B, John R, Glover J.R, McCool & al. Adaptive noise cancelling principles and applications. Proceeding of the IEEE. 1975; 63 (12):1692-1716.

[12] Widrow B, McCool .J.M, Larimore.M.G, Richard Johnson.G. Stationary and nonstationary learning characteristics of the LMS adaptive Filter. Proceeding of the IEEE. 1976; 64 (8): 1151-1162.

[13] Deluca.C.J, Fever.R.S, and Stulen.F.B. Pasteless electrode for clinical use. Med Biol Eng Comput .1979; (17) : 387-390.

[14] Levkov.CH. Fast integer coefficient FIR filter to remove the A.C interference and the high frequency noise component in biological signals.Med Biol Eng Comput. 1989; (27) :330-332.

[15] Kunt. M, Rey.H, Ligtenberg.A. Pre-processing of electrocardiograms by digital technics. Signal Processing. 1982; (4) : 215-222.

[16] Furns. G.S, Tompkins. W.J. A learning filter for removing noise interference. IEEE Trans Biomed Eng. 1983; (30) : 234-235.

[17] Baratta RV, Solomonow M, Zhou B-H, Zhu M. Method to reduce the variability of EMG power spectrum estimates, Journal of electromyography and kinesiology 1998; 8 :279-285.

[18] Bensaadoun Y, Raoof K, Novakov E. Elemination du 50Hz du signal ECG par filtrage adaptatif multidimensionnel. Innov. Techn .Biol .Med, 1994;15 (6) :750-759.

[19] Bahoura M. Hassani S.G. Lee et M. Hubin. Modification de la méthode de Widrow pour l'élimination de l'interférence 50 Hz du signal ECG. Innov. Tech. Biol. Med. 1997; 18 (2): 119-127.

[20] Lindström. L.H and Magnusson. H.N. Interpretation of myoelectric power spectral model and its application. IEEE Trans Biomed Eng. 1976; 65 (5): 653-662.

[21] Raoof K. Traitement du signal electromyographique des muscles respiratoires et estimation des paramètres en temps réel. Joseph fourier University of Grenoble France Phd thesis 1993.

[22] Yacoub S, Ben Brahim J, Ketata R, Gumery P Y, Raoof K. Real time Multidimensional treatments of surface electromyographic signals by electrodes array. Innov. Techn .Biol .Med. 1997;18 (4) :267-275.
[23] Mallat S and Zhang. Z. Matching pursuit with time frequency dictionaries. IEEE Trans Signal Processing. 1993 ; (41) 3397-3415.
[24] Mallat S. Une exploration des signaux en ondelette . Ecole polytechnique 2000.
[25] Davis G, Mallat S and Zhang Z. Adaptive time-frequency decompositions. Optical Engineering, 1994 ; 33 (7): 2183-2191.
[26] Cherkassky V, Kilts S. Myopotential denoising of ECG signals using wavelet thresholding methods. Neural Networks 2001; 14 (8): 1129-1137.
[27] Ping Zhou, Todd A Kuiken. Eliminating cardiac contamination from myoelectric control signals developed by targeted muscle reinnervation. Physiological Measurement 2006; 27: 1311-1327.