Lecture 3 Adaptive Wiener and Biomedical Applications

Contents in the lecture:

1. **Wiener filter**

2. **Adaptive Wiener filter**

1. Wiener filter

Reviewing Wiener filter

2. Adaptive Wiener Filter (AWF)

Introduction

The features of Wiener Filter:

(1) Be suitable to process stationary random signals

(2) The prior statistical properties for signals and noise is required

(3) The parameters of filter system are fixed

Introduction

Kalman Filtering

（1） be suitable to process non-stationary random signals；

（2） The prior statistical properties for signals and noise are required;

（3） The parameters of the filter are time –variation.

Introduction

Biomedical signal analysis in practice

(1) The complexity and non-stationary of biomedical signals;

(2) Be impossible to obtain the prior information of signals and noise; Or

(3) The statistical properties vary with time.

Therefore, Wiener filter and Kaleman filter can not realize the optimum filtering in above situations.

However, Adaptive filter can provide the excellent filtering performances.

Introduction

Adaptive filter concept

By means of the known filter parameters of the previous time, update the filter parameters of the current time to be suitable to the unknown statistical properties of signals and noise for the optimum filter.

Several main adaptive filters

(1) LMS adaptive filter (闭环结构)

(2) RLS (Recursive least – squares)

adaptive filter （开环结构）

(3) IIR adaptive filter

……………

Main applications of AWF

Adaptive Noise Canceling

Adaptive line enhance

LMS adaptive Wiener filter

The LMS adaptive Wiener filter consists of two basic processes:

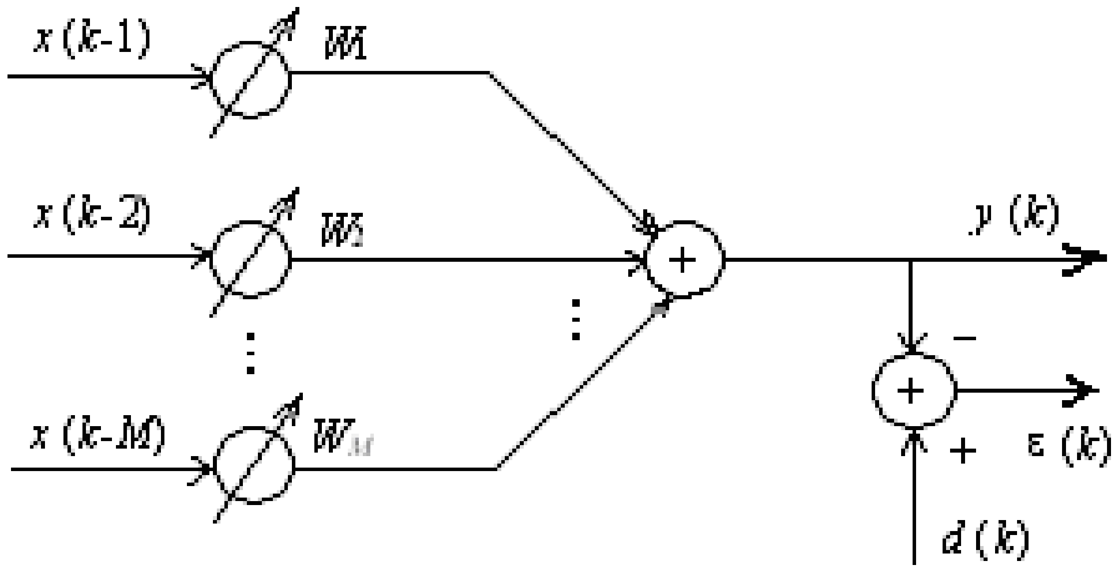
(1) A filtering process (a. input–output;
b. an estimation error) Wiener filtering

(2) An adaptive process (the automatic adjustment of the parameters of the filter in accordance with the estimation error)

LMS adaptive Wiener filter

1 Filtering processing （Wiener filter)

Adaptive linear components:



LMS adaptive wiener filter

LMS principles:

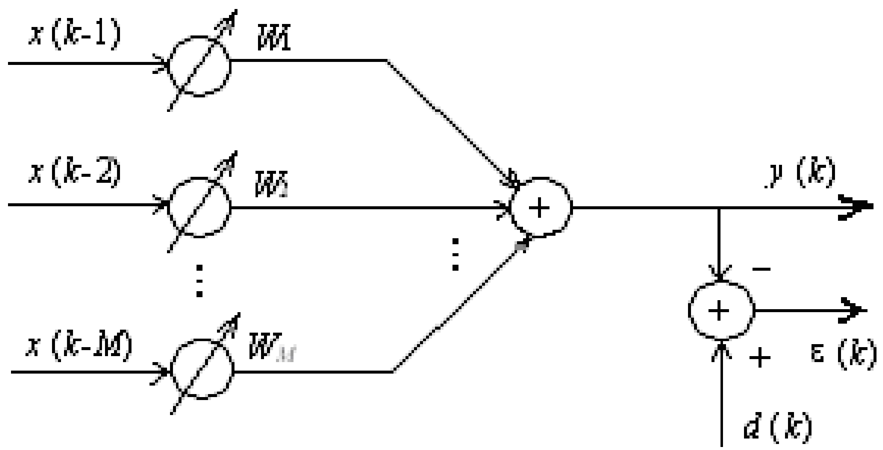
The mean-square value of the error between the output of linear components and the desired response reaches the minimum value.

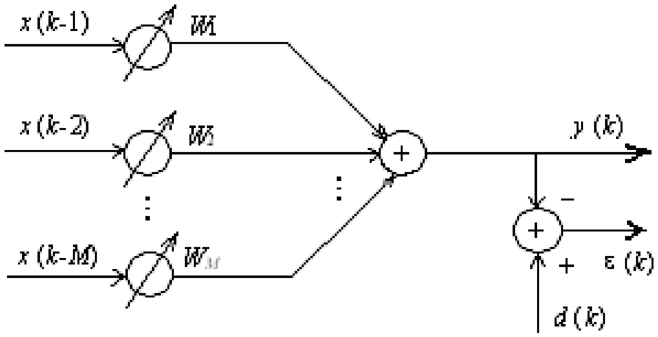
LMS adaptive wiener filter

Input: $X(k) = [X((k-1)T), \cdots, X((k-M)T)]^T$

The weight vector: $W = [W_1, W_2, W_3, \cdots W_m]^T$

Output: $y(k) = \sum_{i=1}^{M} W_i x(k-i)$





Define the error signal:

$$\varepsilon(k) = d(k) - y(k)$$
$$= d(k) - \sum_{i=1}^{M} W_i X(k-i)$$

Its vector expression is

$$\varepsilon(k) = d(k) - W^T X(k)$$
$$= d(k) - X^T(k)W$$

The square value of the error:

$$\varepsilon^2(k) = d^2(k) - 2d(k)X^T(k)W + W^T X(k)X^T(k)W$$

$$\varepsilon^2(k) = d^2(k) - 2d(k)\boldsymbol{X}^T(k)\boldsymbol{W} + \boldsymbol{W}^T\boldsymbol{X}(k)\boldsymbol{X}^T(k)\boldsymbol{W}$$

Taking mathematical expectation，the mean –square error is

$$E\{\varepsilon^2(k)\} = E\{d^2(k)\} - 2E\{d(k)\boldsymbol{X}^T(k)\}\boldsymbol{W} + \boldsymbol{W}^T E\{\boldsymbol{X}(k)\boldsymbol{X}^T(k)\}\boldsymbol{W}$$

Define cross-correlation function vector and auto-correlation function matrix:

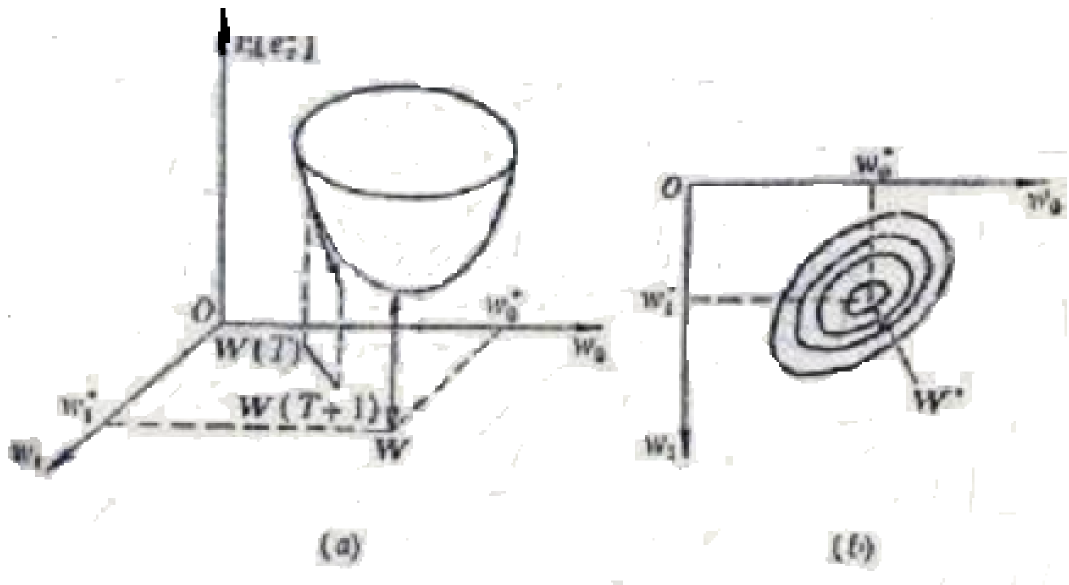
$$R_{xd}^T = E\{d(k)X^T(k)\}$$

$$R_{XX} = E\{X(k)X^T(k)\}$$

The mean-square error can be represented as：

$$E\{\varepsilon^2(k)\} = E\{d^2(k)\} - 2R_{xd}^T W + W^T R_{XX} W$$

The mean square error is a quadratic function of weight coefficient vector W, showed in the following figure.



$$E\{\varepsilon^2(k)\} = E\{d^2(k)\} - 2R_{xd}^T W + W^T R_{xx} W$$

By taking the derivative of the above expression, we have the gradient of the mean-square error function:

$$\nabla(k) = \nabla E\{\varepsilon^2(k)\}$$

$$= \left[\frac{2E\{\varepsilon^2(k)\}}{\partial W_1}, \ldots, \frac{\partial E\{\varepsilon^2(k)\}}{\partial W_M} \right]^T$$

$$= -2R_{xd} + 2R_{xx}W$$

Let $\nabla(k)=0$, the obtained optimum weight Coefficient vector

$$W_{opt} = R_{xx}^{-1} R_{xd}$$

It is Wiener- Hopf standard equation.

$$R_{xx} W = R_{xd}$$

Therefore, optimum weight coefficient vector is also called as Wiener weight coefficient vector.

- **The minimum mean-square error:**

$$E\{\varepsilon^2(k)\}_{\min} = E\{d^2(k)\} - R_{xd}^T W_{opt}$$

- **Analyzing the expression** $W_{opt} = R_{xx}^{-1} R_{xd}$

In order to obtain the optimum weight coefficients:

(1) prior information (e.g. R_{xd})
(2) the inverse operation.

2. The adaptive process

Widrow and Hopf (1960) presented a method for the solution of the optimum weight coefficients. This method has the following advantages:

(1) Simplicity.

(2) The prior information is not required.

(3) The matrix inversion is not required.

The method principle is Widrow and Hopf LMS Algorithm. That is,

$$W(k+1) = W(k) - \mu \nabla(k)$$

where, μ the convergence parameter, which controls convergent speed and the stability of algorithm.

Two keys for LMS algorithm:

(1) Computing the gradient of the mean-square error function

(2) Choosing the convergent parameter

The approximate calculation of $\nabla(k)$

Taking directly $\varepsilon^2(k)$ as the estimation value of the mean-square error $E\{\varepsilon^2(k)\}$, that is

$$\hat{\nabla}(k) = \nabla[\varepsilon^2(k)] = 2\varepsilon(k)\nabla[\varepsilon(k)]$$

where $\nabla[\varepsilon(k)] = \nabla[d(k) - \boldsymbol{W}^T(k)\boldsymbol{X}(k)] = -\boldsymbol{X}(k)$

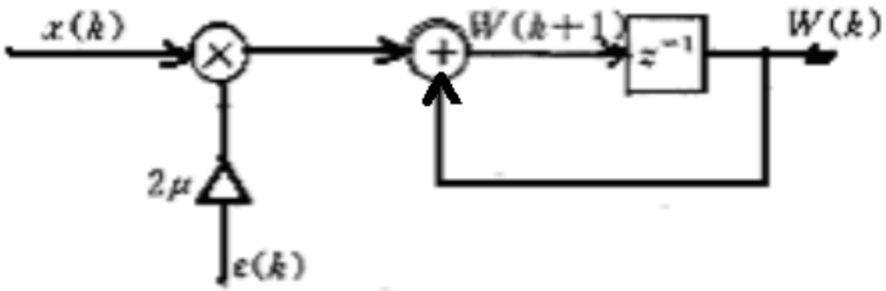
So, the estimation value of the gradient is

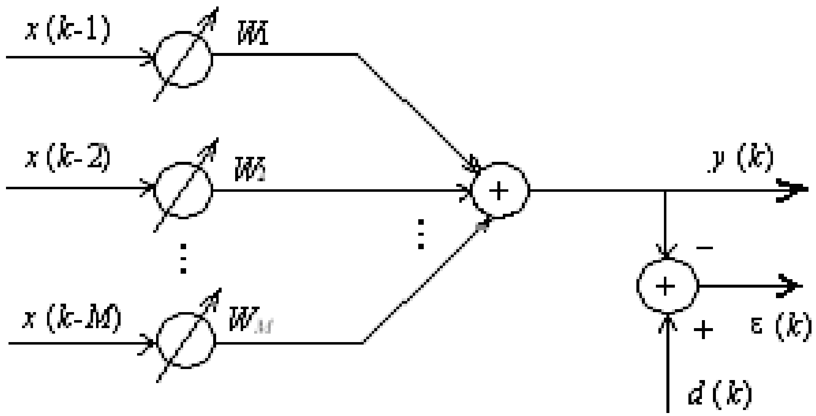
$$\hat{\nabla}(k) = -2\varepsilon(k)\boldsymbol{X}(k)$$

Finally, Widrow – Hopf LMS algorithm is

$$W(k+1) = W(k) + 2\mu\varepsilon(k)X(k)$$

This algorithm can be realized as follows.





Unbiased property analysis for the gradient estimation value $\hat{\nabla}(k)$

- The expectation of $\hat{\nabla}(k)$

$$
\begin{aligned}
E\left\{\hat{\nabla}(k)\right\} &= E\{-2X(k)\varepsilon(k)\} \\
&= -2E\left\{X(k)[d(k) - X^T(k)W(k)]\right\} \\
&= -2[R_{xd} - R_{xx}W(k)] \\
&= \nabla(k)
\end{aligned}
$$

- The results showed that the estimation $\hat{\nabla}(k)$ is unbiased.

Choosing μ

- **The equation for updating the weight coefficients** $W(k+1) = W(k) + 2\mu\varepsilon(k)X(k)$

- **Taking the expectation**

$$E\{W(k+1)\} = E\{W(k)\} + 2\mu E\{\varepsilon(k)X(k)\}$$

$$= E\{W(k)\} + 2\mu E\{X(k)[d(k) - X^T(k)W(k)]\}$$

$$= (I - 2\mu R_{xx})E\{W(k)\} + 2\mu R_{xd}$$

- **Where *I* is unit matrix.**

$$E\{W(k+1)\} = (I - 2\mu R_{xx})E\{W(k)\} + 2\mu R_{xd}$$

- **When k =*0*， there is**

$$E\{\boldsymbol{W}(1)\} = (\boldsymbol{I} - 2\mu \boldsymbol{R}_{xx})E\{\boldsymbol{W}(o)\} + 2\mu \boldsymbol{R}_{xd}$$

- **When k = *1*， there is**

$$E\{\boldsymbol{W}(2)\} = (\boldsymbol{I} - 2\mu \boldsymbol{R}_{xx})E\{\boldsymbol{W}(1)\} + 2\mu \boldsymbol{R}_{xd}$$

$$= (\boldsymbol{I} - 2\mu \boldsymbol{R}_{xx})^2 E\{\boldsymbol{W}(0)\} + 2\mu \sum_{i=0}^{1} (\boldsymbol{I} - 2\mu \boldsymbol{R}_{xx})^i \boldsymbol{R}_{xd}$$

$$E\{W(0)\} = W(0)$$

So

$$E\{W(2)\} = (I - 2\mu R_{xx})^2 W(0) + 2\mu \sum_{i=0}^{1} (I - 2\mu R_{xx})^i R_{xd}$$

Repeating the above iteration till $k+1$, there is

$$E\{W(k+1)\} = (I - 2\mu R_{xx})^{k+1} W(0) + 2\mu \sum_{i=0}^{k} (I - 2\mu R_{xx})^i R_{xd}$$

The following conclusions will be used for later Analysis.

- 1、 $R_{xx} = Q\Sigma Q^T = Q\Sigma Q^{-1}$

  syemmtry

  $Q^{-1} = Q^T$

  $\Sigma = diag(\lambda_1, \cdots, \lambda_M)$

  λ_i **is the eigenvalue of** R_{xx}

2、

$$
\begin{aligned}
(I - 2\mu Q\Sigma Q^{-1})^i &= (QQ^{-1} - 2\mu Q\Sigma Q^{-1})^i \\
&= [Q(I - 2\mu\Sigma)Q^{-1}]^i \\
&= Q(I - 2\mu\Sigma)Q^{-1} \\
&\quad \cdots Q(I - 2\mu\Sigma)^i Q^{-1} \\
&= Q(I - 2\mu\Sigma)^i Q^{-1}
\end{aligned}
$$

（3） $$\lim_{k \to \infty} \sum_{i=0}^{k} (I - 2\mu Q \Sigma Q^{-1})^{i} = \sum_{i=0}^{\infty} Q(I - 2\mu \Sigma) Q^{-1}$$

$$= Q[(2\mu\Sigma)^{-1}]Q^{-1}$$

（4） **By choosing μ, all λ_i is less than 1, that is,** $|1 - 2\mu\lambda_{max}| < 1$

We have: $$\lim_{k \to \infty} (I - 2\mu\Sigma)^{k+1} = 0$$

（5） $$R_{xx}^{-1} = Q\Sigma^{-1}Q^{-1}$$

According to Equation (1), there is：

$$E\{W(k+1)\} = (I - 2\mu Q\Sigma Q^{-1})^{k+1}W \quad + 2\mu\sum_{i=0}^{k}(I - 2\mu Q\Sigma Q^{-1})^{i}R_{xd}$$

According to Equation (2), (3), (4) and (5), there is

$$E\{W(k+1)\} = Q\Sigma^{-1}Q^{-1}R_{xd}$$

$$= R_{xx}^{-1}R_{xd} = W_{opt}$$

- **With $k \rightarrow \infty$, the mathematical expectation of weight vector converge to Wiener solution when the following Equation is satisfied.**

$$|1 - 2\mu\lambda_{max}| < 1$$

- or

$$0 < \mu < \frac{1}{\lambda_{max}}$$

The convergence factor statisfies：

$$0 < \mu < \frac{1}{\lambda_{max}}$$

- λ_{max} represents the maximum eigenvalue in R_{xx};
- In practical application, computing R_{xx} for μ or setting the parameter μ through exploring many times.
- If μ value is small, the convergence can be ensured, but the convergent speed is very slow.
- In contrast，if μ value is large，the convergent speed can be increased, but it is possible to converge to the noise.

LMS adaptive algorithm (software realization)

初始化:

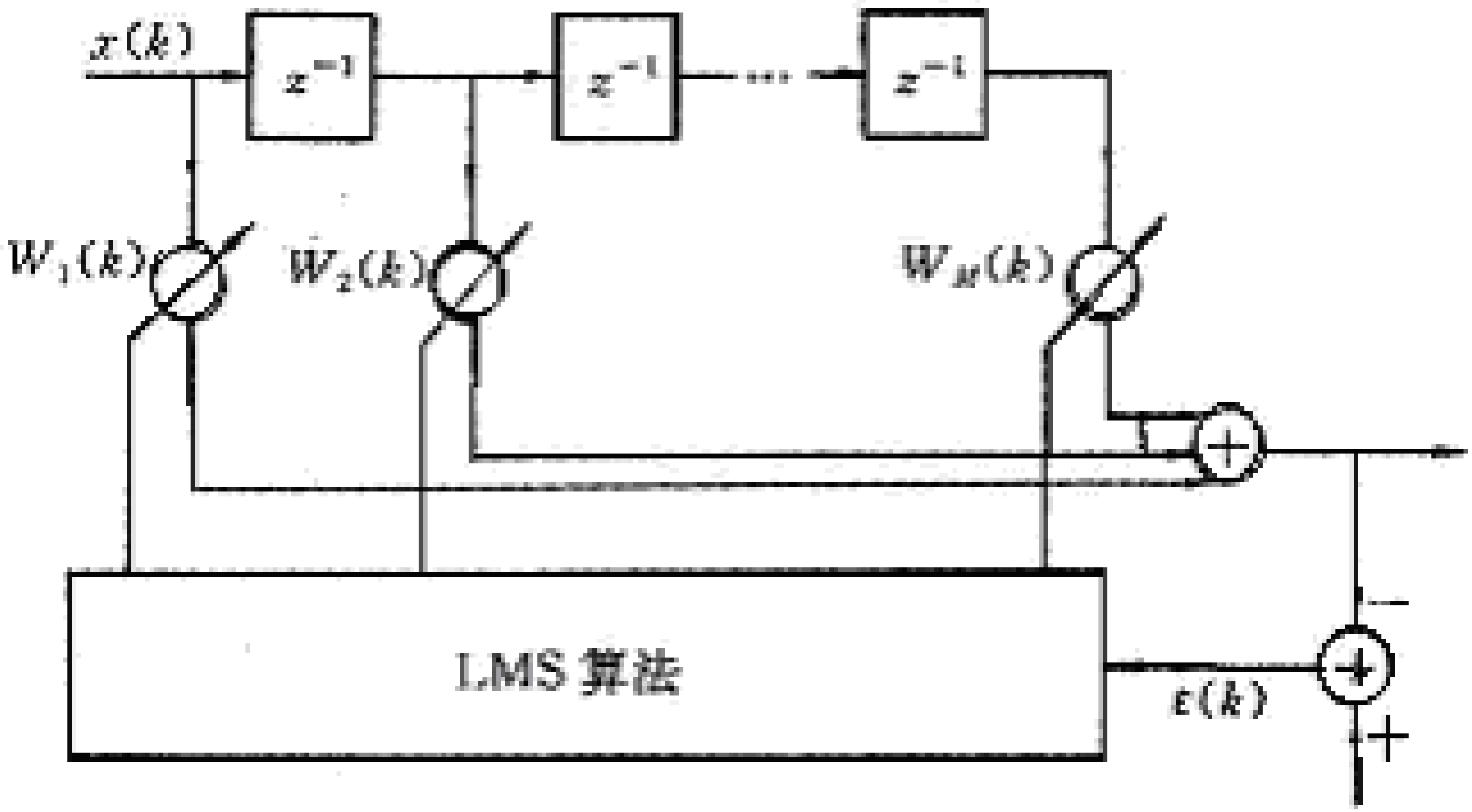
$$W(0)=0;$$
$$R(0)=I;$$

选择 $\mu: 0<\mu<\dfrac{1}{\lambda_{max}}$

$For\ k=1\ \ to\ \ n\ final\ do:$

$$W(k)=W(k-1)+2\mu[d(k)-W^T(k-1)X(k)]X(k)$$

LMS adaptive filter （hardware realization）



RLS Adaptive Filter

- **LMS adaptation algorithm is an efficient and simple approach.**
- **However, the speed of convergence is inappropriate for the fast-varying signals due to its slow convergence properties.**
- **RLS Adaptive algorithm is based on least – squares criteria and has fast convergence and stable filter characteristics.**

Homework 3

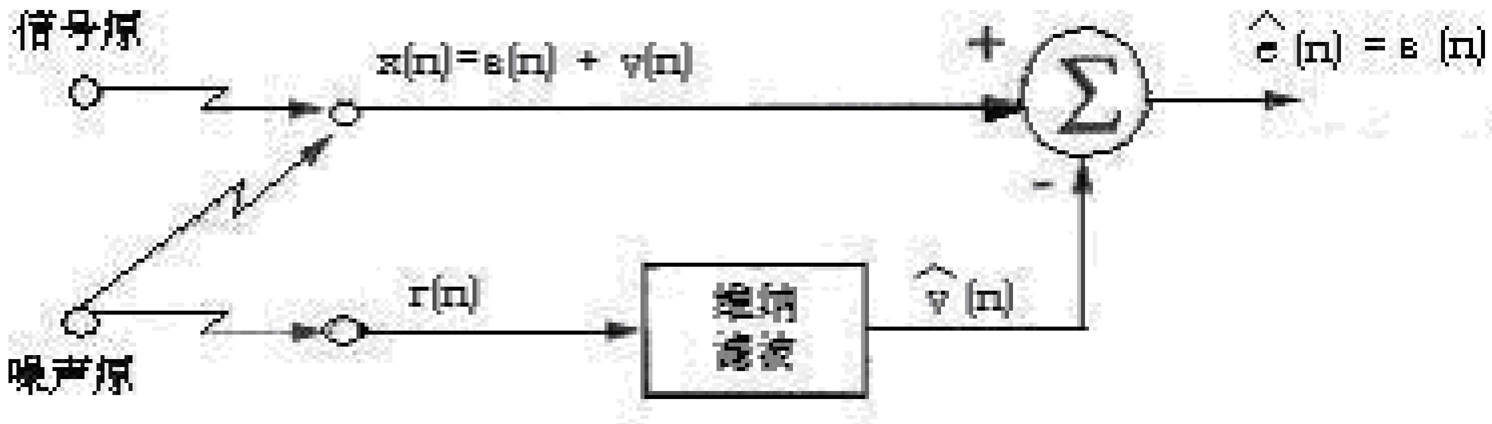
- 写出RLS Adaptive Filter误差准则公式，注明公式中每个符号的意义。比较LMS和RLS Adaptive Filters。

3. Adaptive Noise Cancelling (ANC)

ANC structure: the main and reference channels

Suppose that main signal consist of the useful signal and noise;
ANC technique estimates the noise in the reference channel and canceling the noise from main signal.

3. ANC Principle
Optimum noise canceling (ONC)



- **where**

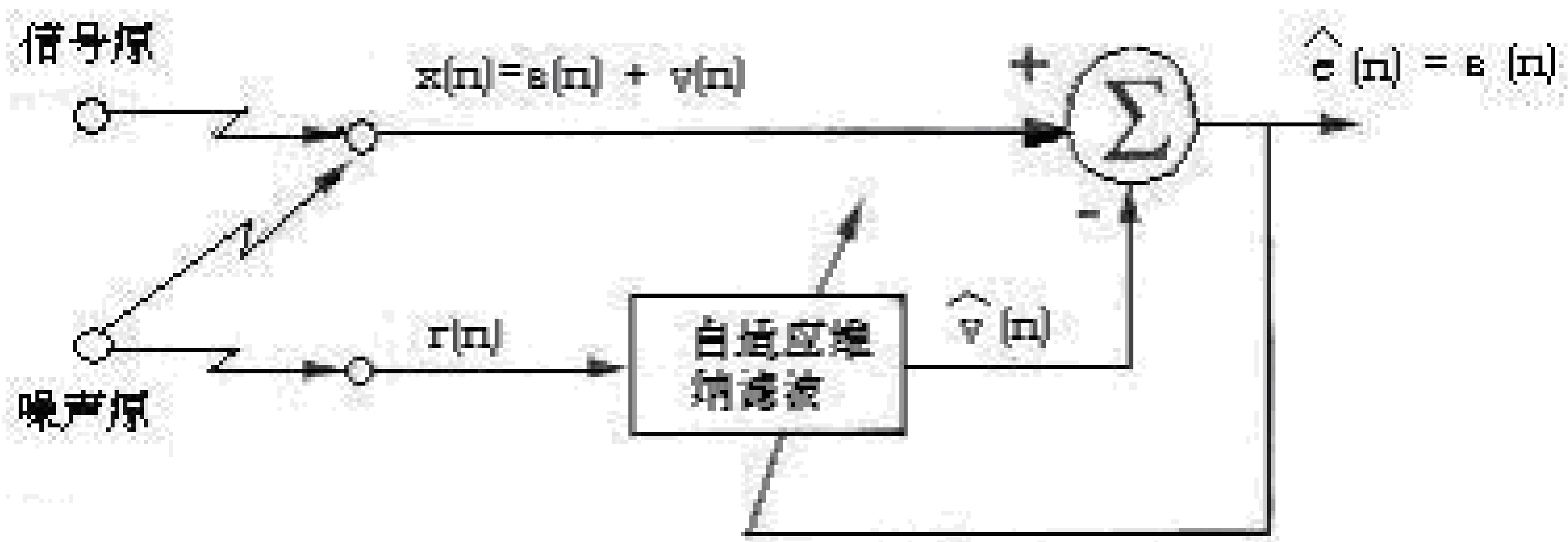
$$\hat{v}(n)=\sum_{m=0}^{M} w_M r(n-m)$$

$$= w_0(n)r(n)+w_1(n)r(n-1)+\cdots+w_M(n)r(n-M), \qquad 0\le m\le M$$

- **The estimation error *e* (*n*)**

$$e(n)=x(n)-\hat{v}(n)=x(n)-w^T(n)r(n)$$

Adaptive Noise Cancelling ANC

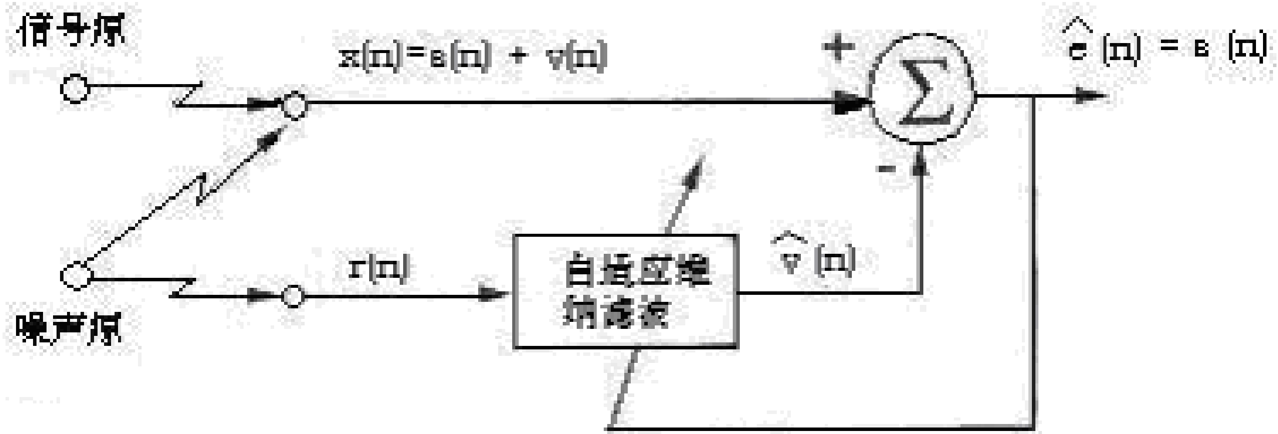


3.1 ANC based on LMS

- According to the inference in section 2, the iteration expression for updating filter weight $w_m(n)$

$$W(k+1) = W(k) + 2\mu e(k) X(k)$$

$$w_m(n+1) = w_m(n) + 2\mu e(n) r(n-m) \qquad 0 \le m \le M$$



LMS adaptiv noise canceling algorithm

第一步：设一个初值$w_m(0)$； $$w_m(n+1)=w_m(n)+2\mu e(n)r(n-m) \qquad 0\le m\le M$$

第二步： 计算自适应 FIR 滤波器的输出$\hat{v}(n)$，

$$\hat{v}(n)=\sum_{m=0}^{M} w_m(n)r(n-m)$$

其中，M表示滤波器的阶。

第三步：估计当前时刻 n 的误差$e(n)$，

$$e(n)=x(n)-\hat{v}(n)\approx\hat{s}(n)$$

第四步：用最速下降 LMS 算法更新滤波器权重$w_m(n)$ ：

$$w_m(n+1)=w_m(n)+2\mu e(n)r(n-m) \qquad 0\le m\le M$$

第五步：校验误差是否满足标准。若满足标准，则停止迭代。若不满足，则进行下一步；

第六步：$n\to n+1$，到下一个时刻，重复以上步骤，直至满足要求为止。

Application Example

If the reference input, *r*(*n*), is sinusoidal with frequency, ω_0, the adaptive filter will eliminate any sinusoidal components with frequency ω_0 from the main signal. In this case, the adaptive filter acts as an adaptive notch filter. Analyze the adaptive notch filter operation principle.

先假定参考输入信号 $r(n)$ 为

$$r(n)=e^{j\omega_0 n}$$

代入式 $w_m(n+1)=w_m(n)+2\mu e(n)r(n-m) \qquad 0\le m\le M$ 得，

$$w_m(n+1)=w_m(n)+2\mu e(n)e^{-j\omega_0(n-m)} \qquad m=0,1,\ldots\ldots M \tag{1}$$

(1)式 中的 $w_m(n)$ 由下式給出，

$$w_m(n)=y_m(n)e^{-j\omega_0(n-m)} \tag{2}$$

将式(2)代入式(1) 得

$$y_m(n+1)e^{-j\omega_0}=y_m(n)+2\mu e(n) \tag{3}$$

式(3)两边同时取 Z 变換得

$$zY_m(z)e^{-j\omega_0}=Y_m(z)+2\mu E(z) \tag{4}$$

于是

$$Y_m(z)=E(z)\frac{2\mu e^{j\omega_0}}{z-e^{j\omega_0}} \tag{5}$$

被估计的信号 $\bar{v}(n)$ 由下式定义为

$$\bar{v}(n)=\sum_{m=0}^{M} w_m(n)r(n-m)=\sum_{m=0}^{M} w_m(n)e^{j\omega_0(n-m)} \tag{6}$$

将式 (2) 代入式 (6) 得

$$\bar{v}(n)=\sum_{m=0}^{M} y_m(n) \tag{7}$$

式 (7) 两边同时取 Z 变换，并利用式 (5) 有

$$\bar{V}(z)=E(z)\frac{2\mu(M+1)e^{j\omega_0}}{z-e^{j\omega_0}} \tag{8}$$

输出 $e(n)$能被估计为

$$e(n)=x(n)-\hat{v}(n) \tag{9}$$

取式 (9) 的 Z 变换有

$$E(z)=X(z)-E(z)\frac{2\mu(M+1)e^{j\omega_0}}{z-e^{j\omega_0}} \tag{10}$$

转移函数 $H(z)$ 能被估计为

$$H(z)=\frac{E(z)}{X(z)}=\frac{z-e^{j\omega_0}}{z-e^{j\omega_0}(1-2\mu(M+1))} \tag{11}$$

很明显，式 (11) 在 $z=e^{j\omega_0}$ 处有一个零点，这表明槽形滤波器将滤除主信号 $x(n)$ 中频率为ω_0 的成分。从式（8-2-32）还可发现，较小 μ 值将使滤波器的所有极点落在单位园内，从而使滤波器稳定。基于最小均方误差准则(LMS)的自适应噪声抵消算法的样本程序可在很多参考书中找到。

Adaptive Line Enhancer (ALE)

- Introduction

  The disadvantage of ANC:

  The reference channel is required. In practice, it is not always possible to provide a good reference channel.

ALE is actually an improvement of ANC.

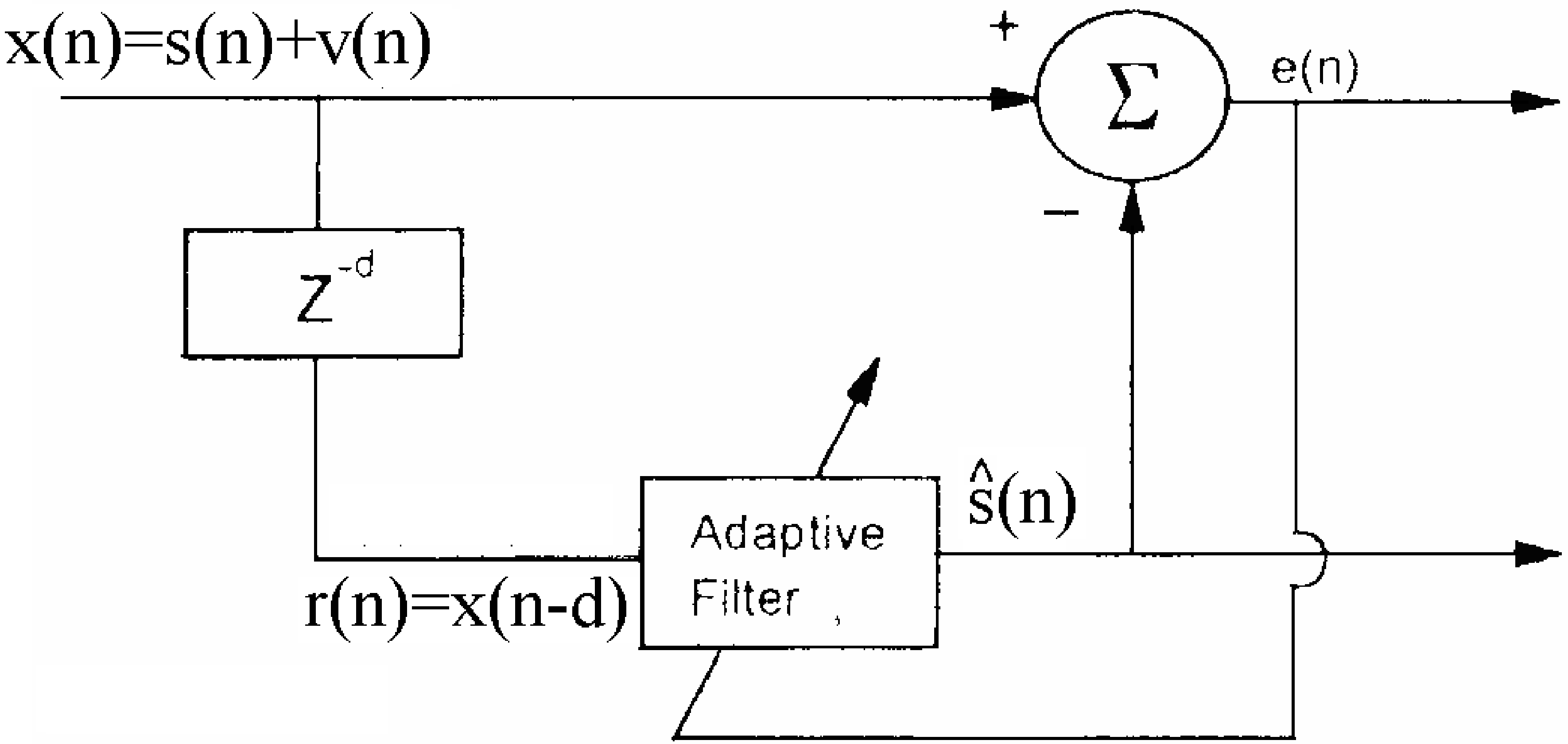
ALE Method Using the LMS Algorithm

The difference between the ALE and the ANC is as follows:

The second or reference input of the ANC is a delayed replica of the main input.

This delay signal is processed through the FIR filter to calculate the best estimate of the desired signal buried in the noise.

ALE Method Using the LMS Algorithm



The function of ALE

(1) To decorrelate the noise components in the secondary input from those in the primary input.

(2) To separate the noise signal from the desired signal by acting as a “self-tuning” filter.

ALE Method Using the LMS Algorithm

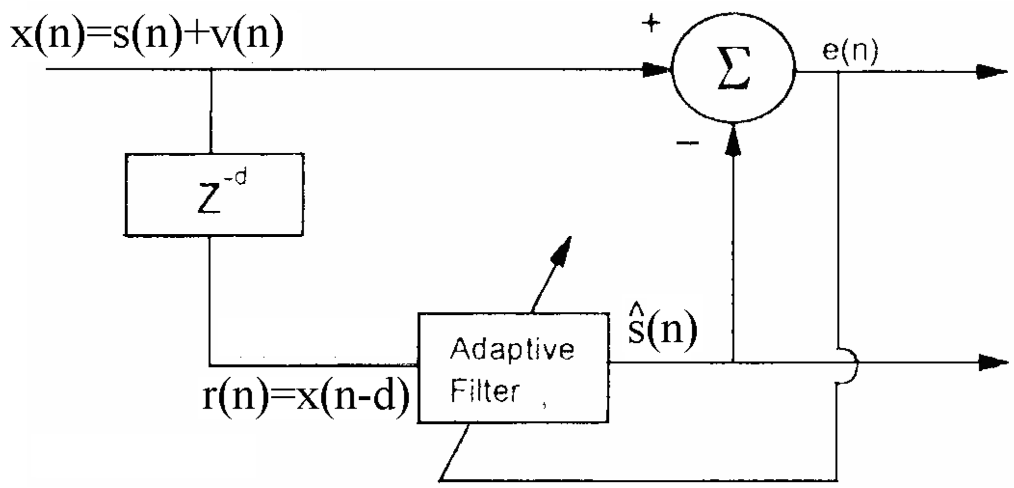
$$x(n) = s(n) + v(n) \qquad (1)$$

$$r(n) = x(n-d) = s(n-d) + v(n-d) \qquad (2)$$

$$\hat{s}(n) = \sum_{m=0}^{M} w_m(n) r(n-m) \qquad (3)$$

$$= \sum_{m=0}^{M} w_m(n) x(n-m-d)$$

$$e(n) = s(n) - \hat{s}(n)$$



Adaptive ALE algorithm based on the LMS

- **Step 1. Calculate the estimated signal**

$$\hat{s}(n) = \sum_{m=0}^{M} w_m(n)\, x(n-m-d)$$

- **Step 2. Estimate the error signal at the output,**

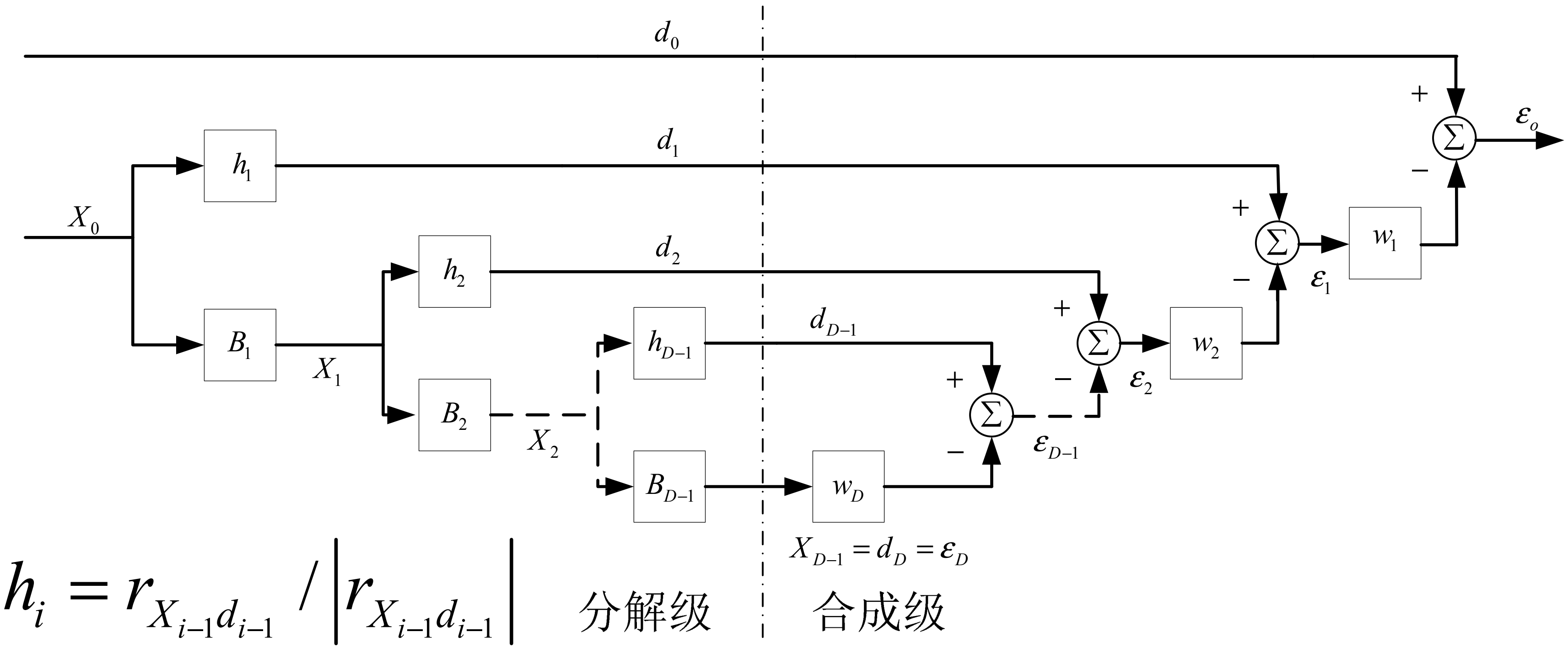
$$e(n) = s(n) - \hat{s}(n)$$

- **Step 3. Update the ALE filter coefficients, at the *nth* stage**

$$w_m(n+1) = w_m(n) + 2\mu e(n)\, x(n-m-d) \qquad m = 0,1,2,\ldots,M$$

- **Step 4. Go to the next stage.**

Multiple Wiener Filter based on Noise Canceling



$$h_i = r_{X_{i-1}d_{i-1}} / \left| r_{X_{i-1}d_{i-1}} \right|$$

$$B_i h_i = 0$$

$$B_i = I - h_i h_i^H$$

Biomedical applications

- ANC method to enhance ECG monitoring
- ANC method to enhance Fetal ECG Monitor
- ANC method to enhance Electrogastric Measurements

1. The adaptive noise canceling method to enhance ECG monitoring

Clinical problems:

ESU（An electrosurgical unit, a medical device)

Applications: (1) cutting tissue;

(2) coagulating severed blood vessels

ESU produces a radiaofrequency (RF) signal modulated at 120 Hz and 100-120W of broad –band spectral power.

100-400V transient voltage over the patient’s skin surface.

ECG monitor can detect the large ESU voltage (interference) present at the patient’s skin surface.

Signal-to-noise ratio: S/N = -90 dB

1. The adaptive noise canceling method to enhance ECG monitoring

Clinical problems:

In addition, small amount of patient motion, which change spatial relationships, also induce random low-frequncy modulation to the entire ESU current.

Yelderman et al proposed an adaptive noise canceling method:
(1) enhance ECG monitoring;
(2) eleminates 60Hz power line interference from ECG.

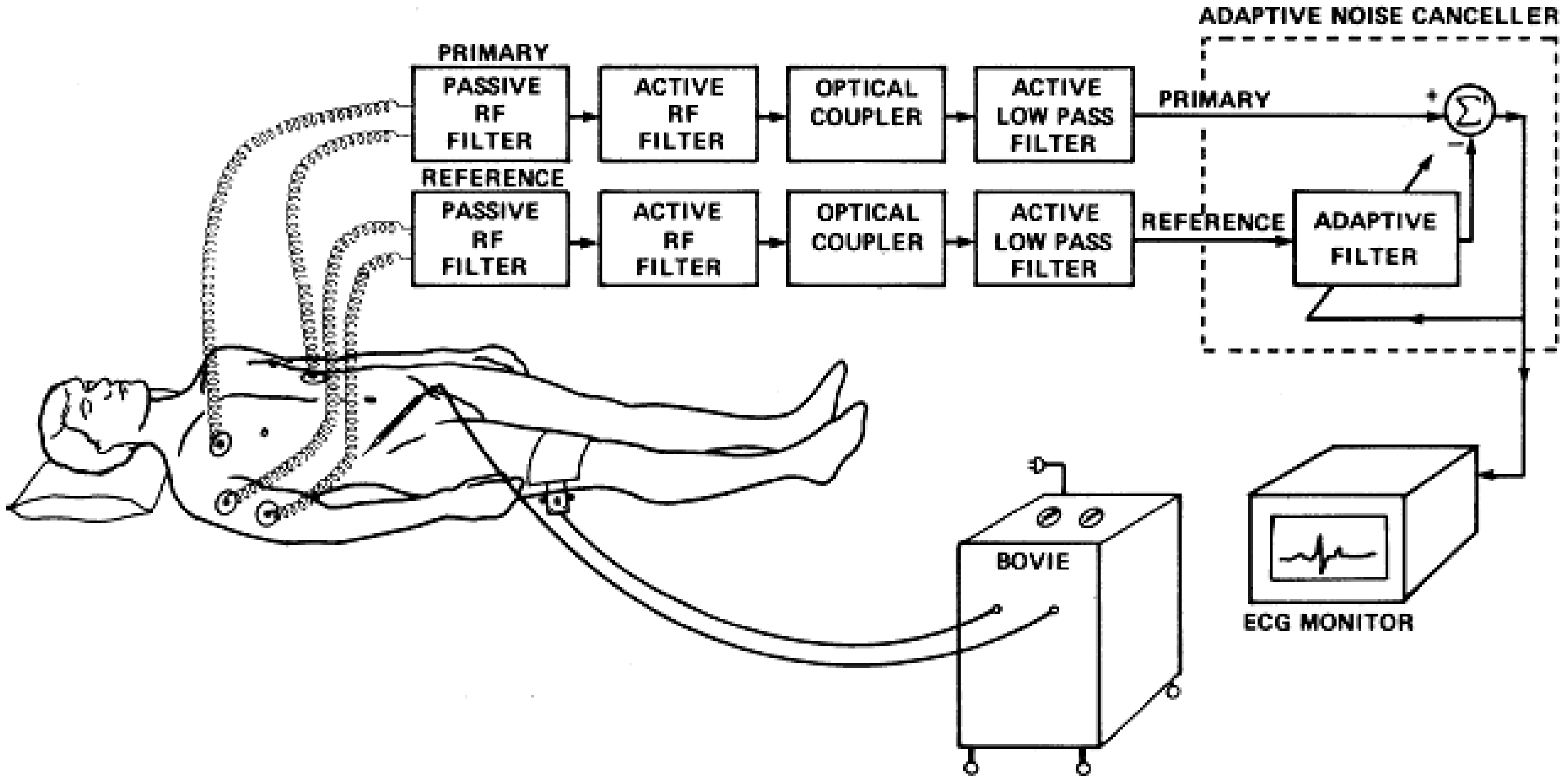


Fig. 2. ECU interference rejection system.

(1) The main electrodes receive the maximum ECG signal and the interference from ESU when it is energized.
(2) The reference electrodes receive the ESU interference while at the same receiving a minimal amount of ECG signal.

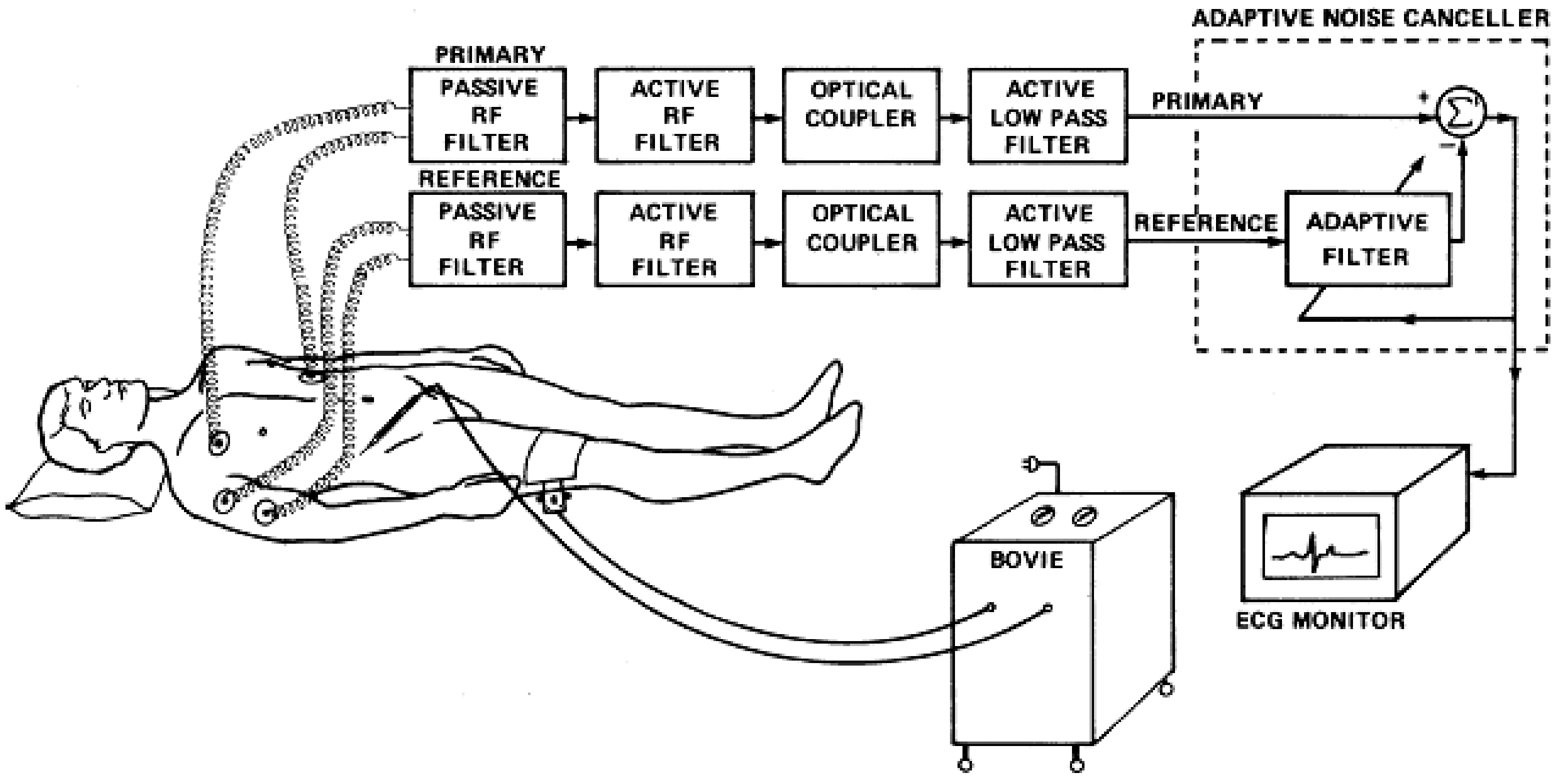


Fig. 2. ECU interference rejection system.

Two steps in the method

- **Step 1:**

(1) eliminating the high–voltage RF noise by passive RF filters with high-impedance load;

(2) eliminating any remaining noise signal above 600Hz.Low-pass filters were used to eliminate all remaining spectral components above approximately 600 Hz.

(3) Optical couple were used to remove remaining common mode RF interference.

Two steps in the method

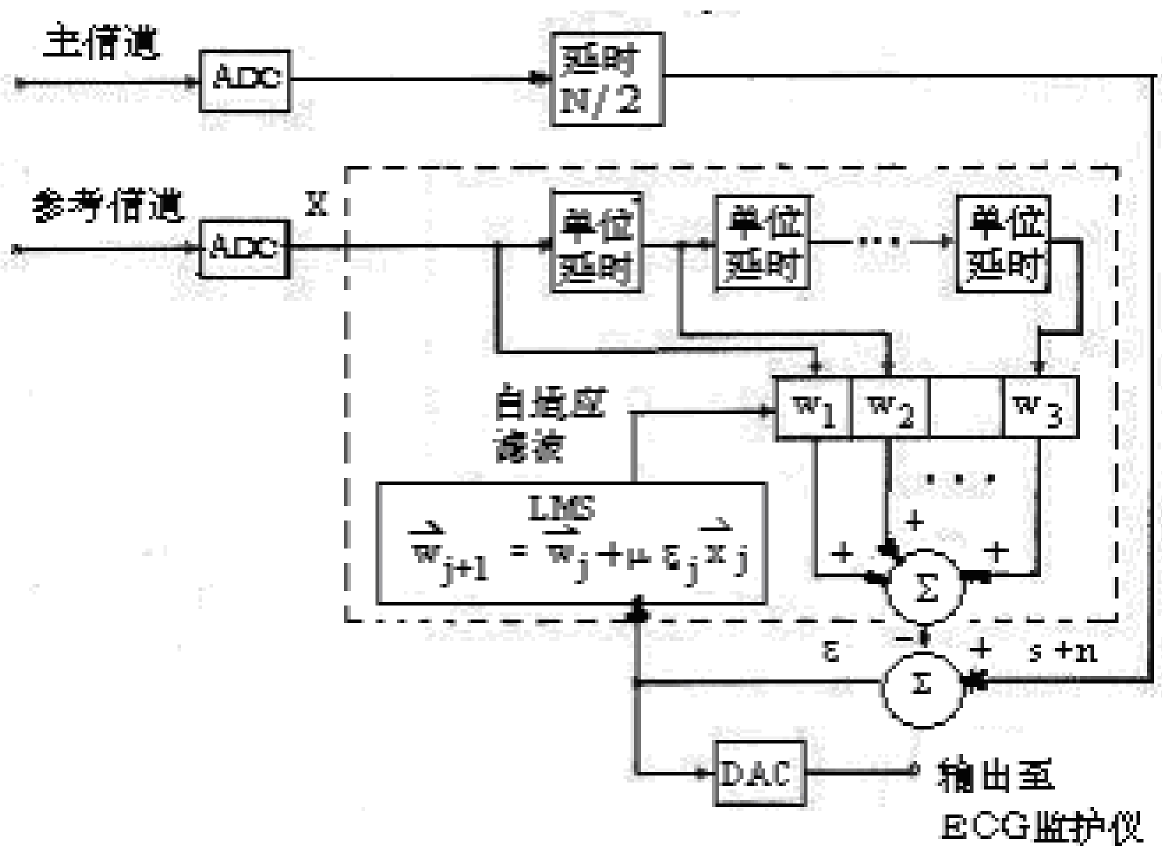
Step 1:

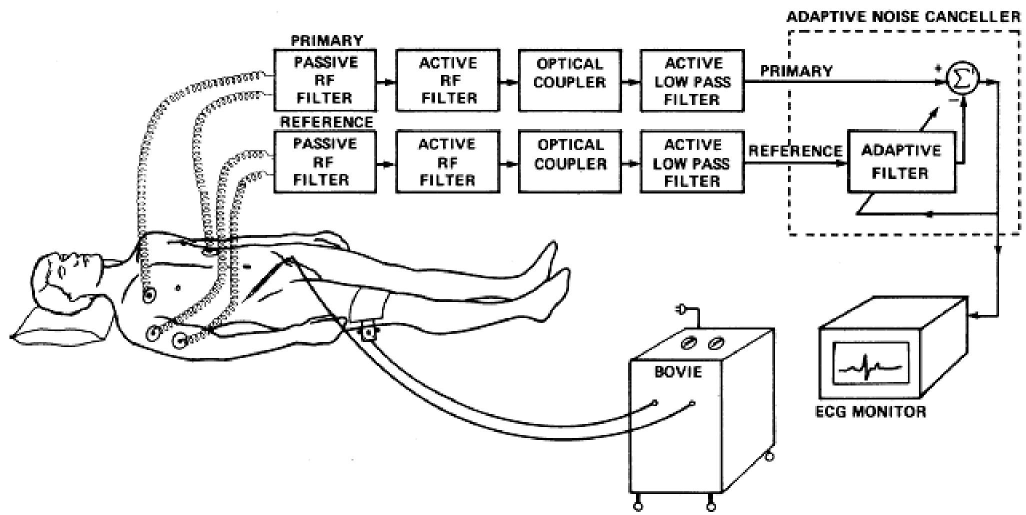
- **Results: SNR radio was improved from -90dB to -10dB, but strong interference noise at low frequencies 60, 120, 180Hz still exist.**

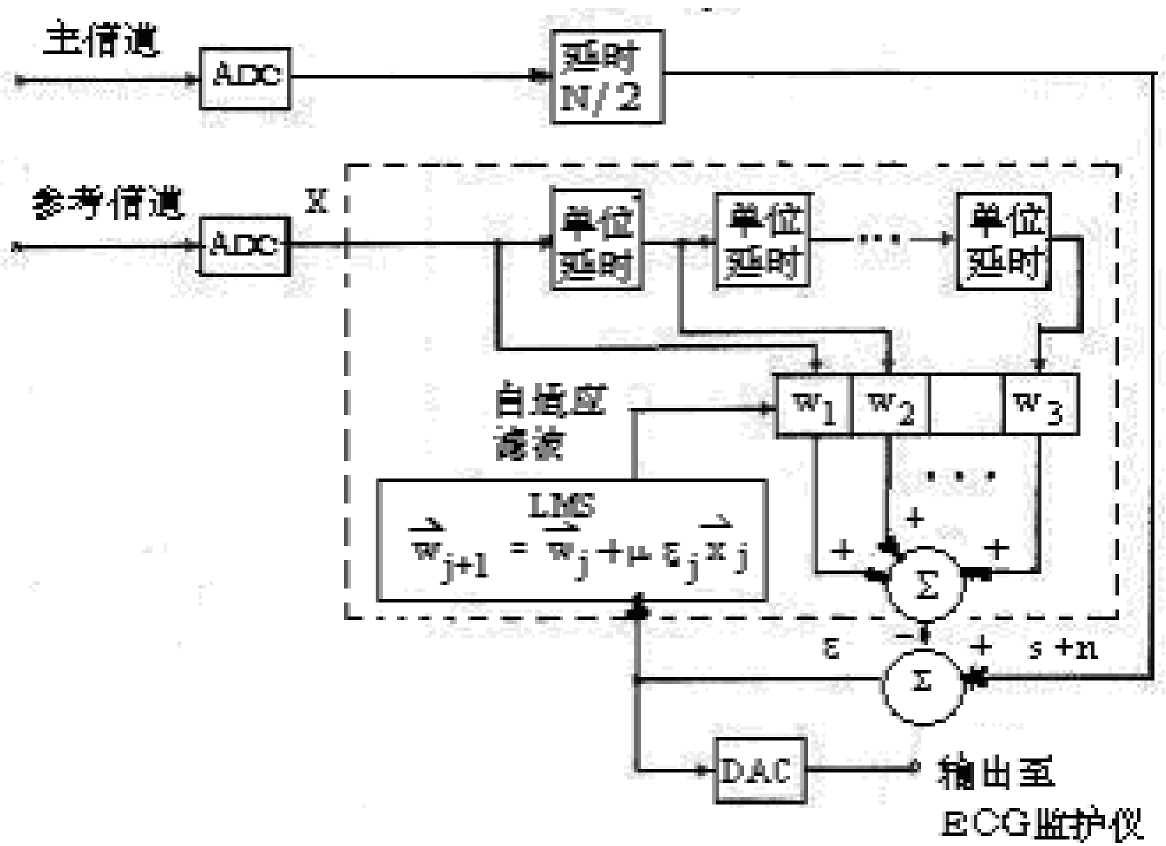
- **Increased SNR: 80dB**

- **Step 2: Eliminating strong low frequency interference using ANC methods, which is superior to that of fixed, tuned notch filters.**

A digital ANC realization block-diagram

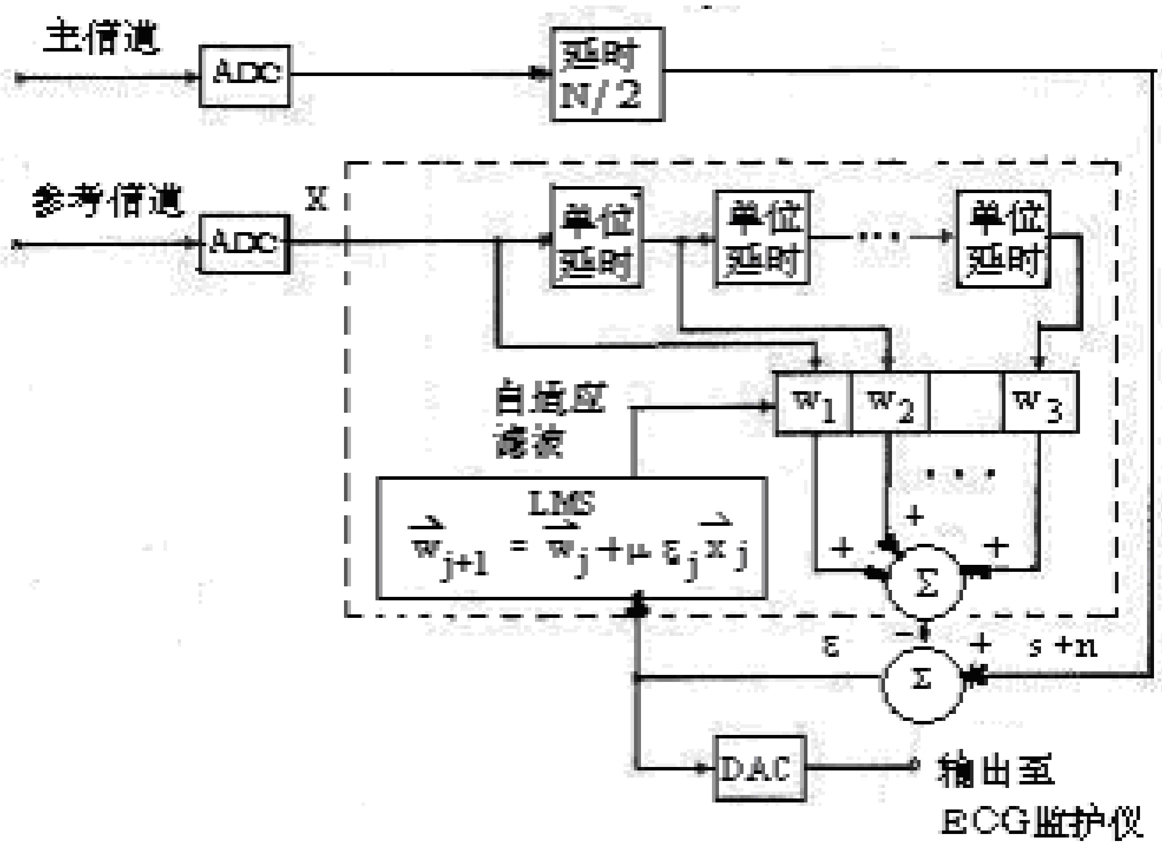



ADAPTIVE NOISE CANCELLER
PRIMARY
PASSIVE RF FILTER
ACTIVE RF FILTER
OPTICAL COUPLER
ACTIVE LOW PASS FILTER
PRIMARY
REFERENCE
PASSIVE RF FILTER
ACTIVE RF FILTER
OPTICAL COUPLER
ACTIVE LOW PASS FILTER
REFERENCE
ADAPTIVE FILTER
BOVIE
ECG MONITOR


主信道
ADC
延时 N/2
参考信道
X
ADC
单位延时
单位延时
单位延时
w_1
w_2
w_3
自适应滤波
LMS
$\vec{w}_{j+1} = \vec{w}_j + \mu \varepsilon_j \vec{x}_j$
Σ
ε
$s+n$
Σ
DAC
输出至 ECG监护仪

- A digital ANC realization block-diagram in Step 2.
- Increased SNR: 30dB

The final SNR: 20dB



Conclusion 1:

Yeldman et al showed that it is impossible to eliminate all interference noise from the ECG using only the ANC without any preprocessing filters.

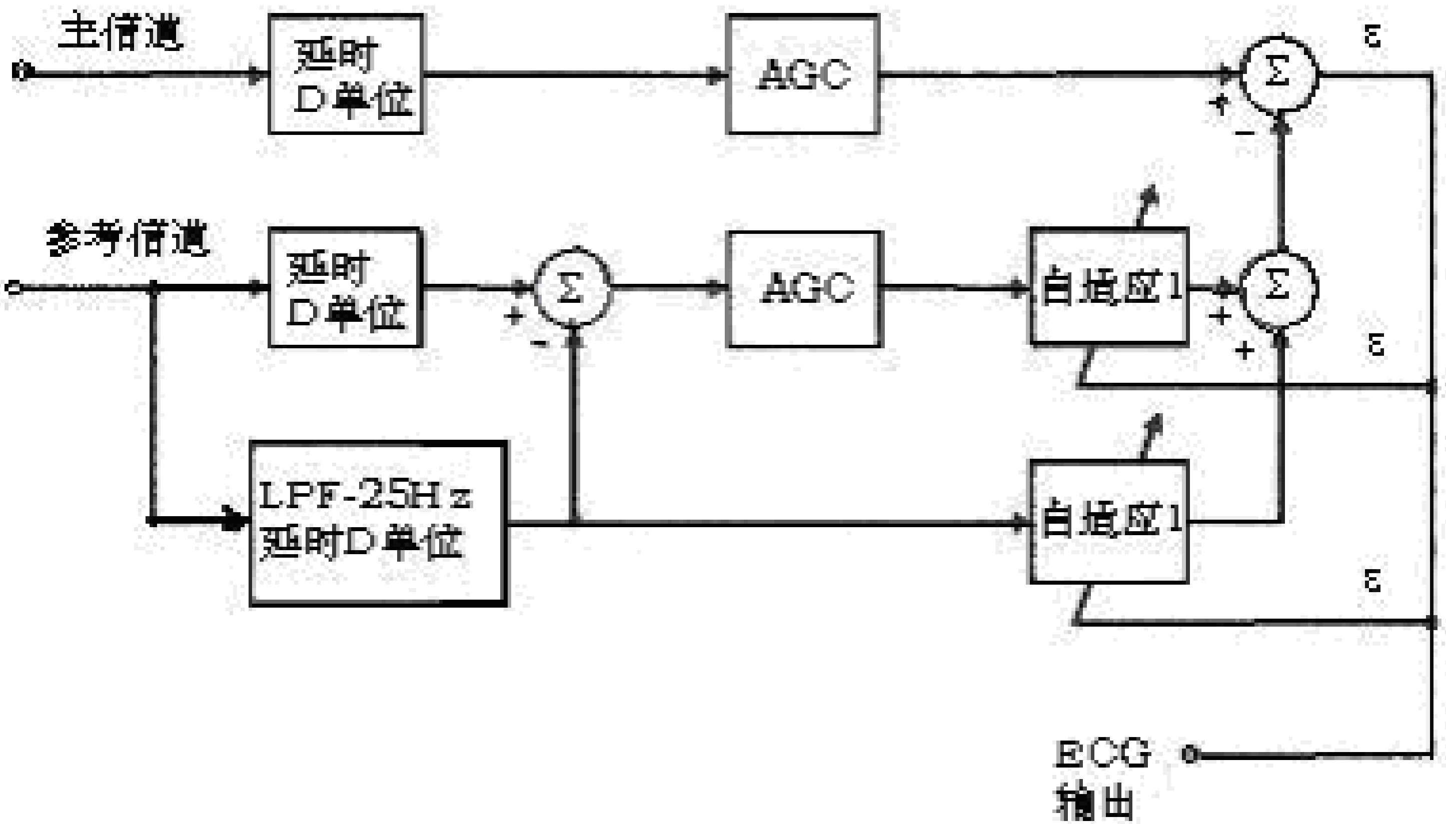
Step 2:
Analyzing the remaining noise characteristics

(1) Low-frequency interference（<25Hz）from RF current flow.

(2) 60Hz、120Hz power line frequency distortion

Thus, using dual reference channels because there are two different interference.

Dual reference adaptive noise canceler block-diagram



Experimatal Results

Sampling rate: 400Hz；$0.02 < \mu < 0.2$

(1) Coagulation

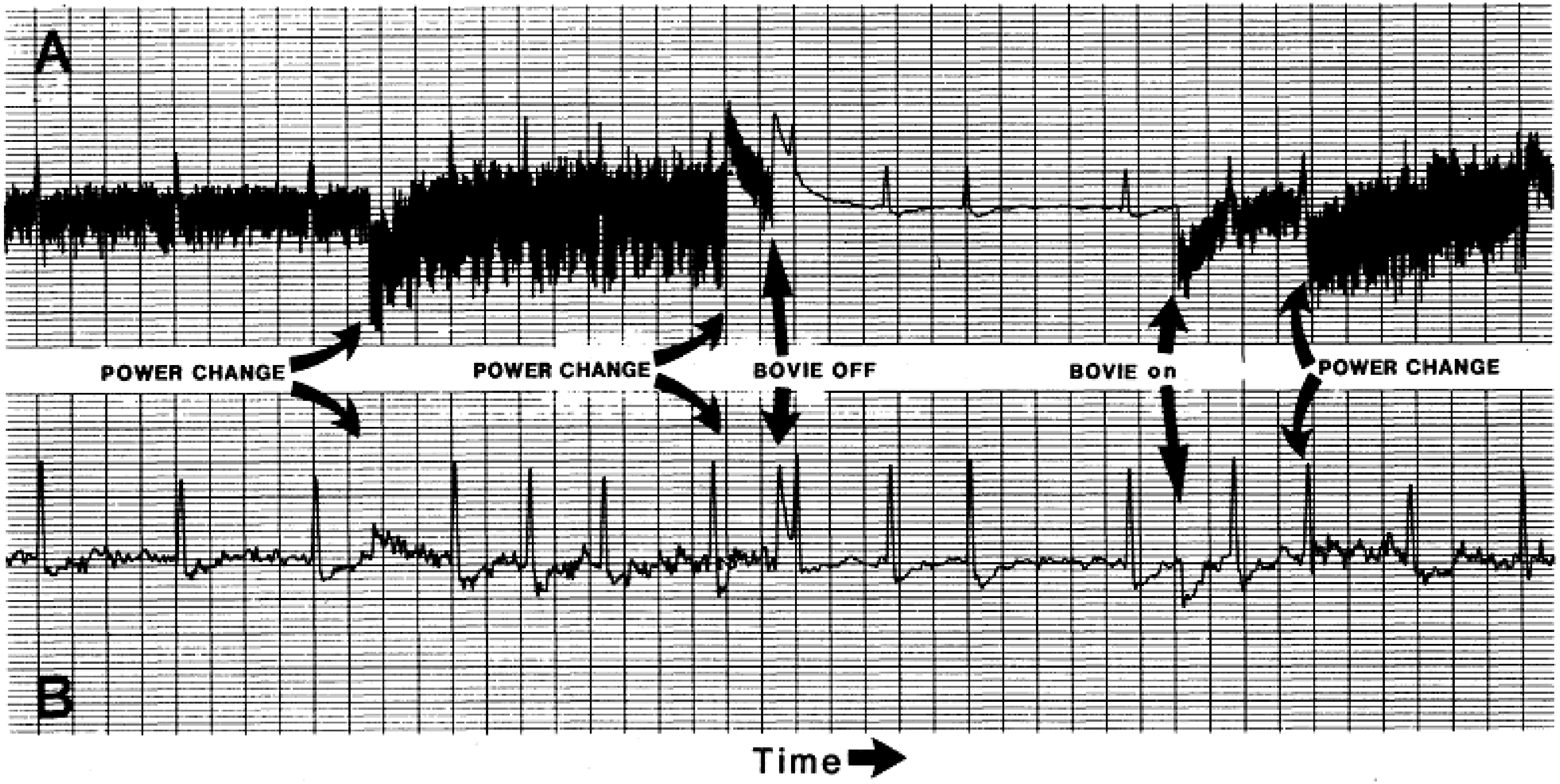


Fig. 5. Cancellation/coagulation.

Experimatal Results
Sampling rate: 400Hz; $0.02 < \mu < 0.2$
(2) Cut

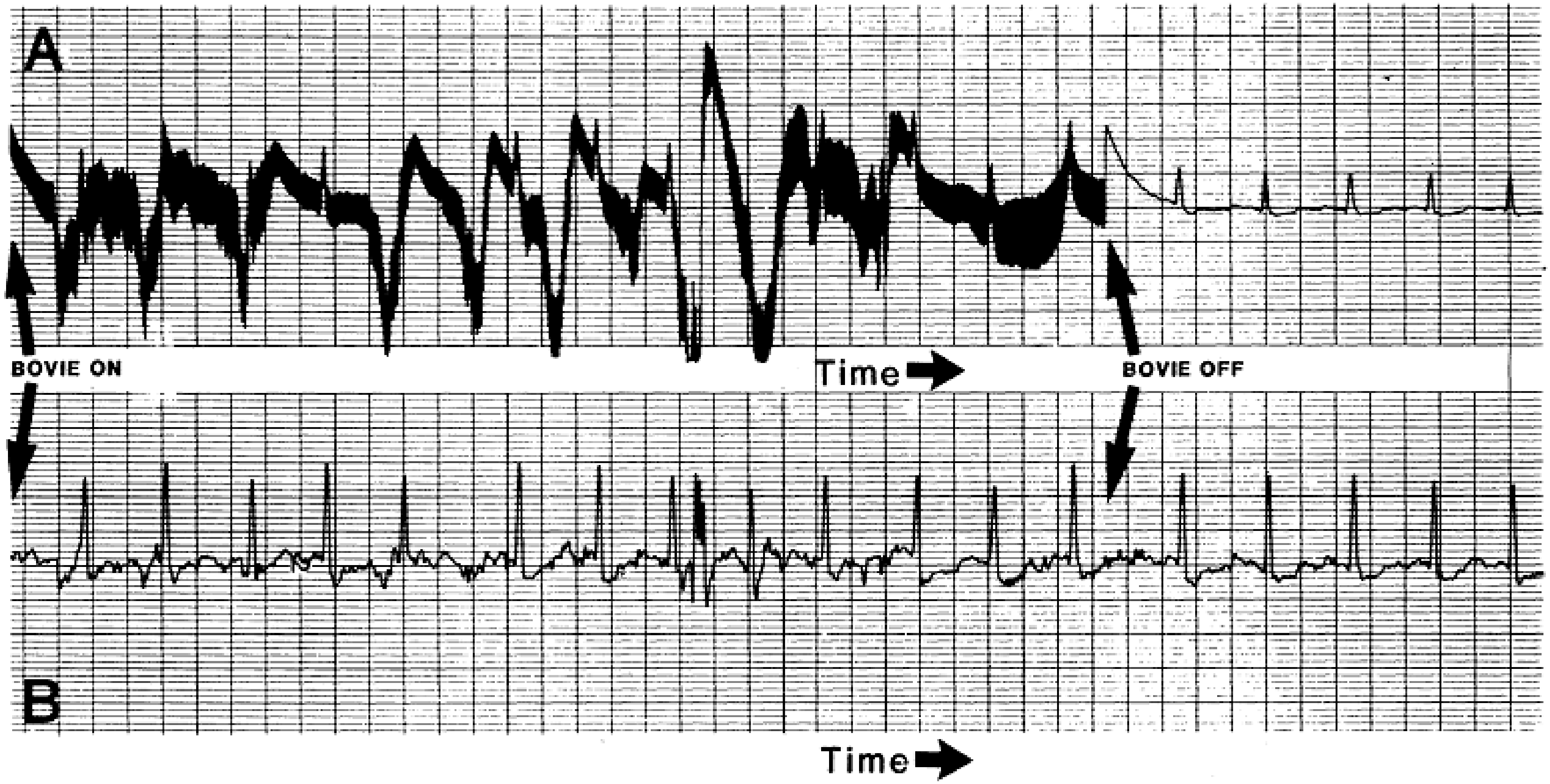


Fig. 6. Cancellation/cut.

Conclusions

(1) The preprocessing of biomedical signals before adaptive filtering may be necessary to eliminate high-frequency interference noise.

(2) Results showed that the combination of analog/digital filters and the ANC is effective in retrieving the ECG signal from the background noise.

2. ANC method to Enhance Fetal ECG Monitoring

- **Clinical Problem：**

In practical, fetal heart rate and number of fetuses are detected by recording abdominal ECG during labor and delivery.

The effects of following factors:

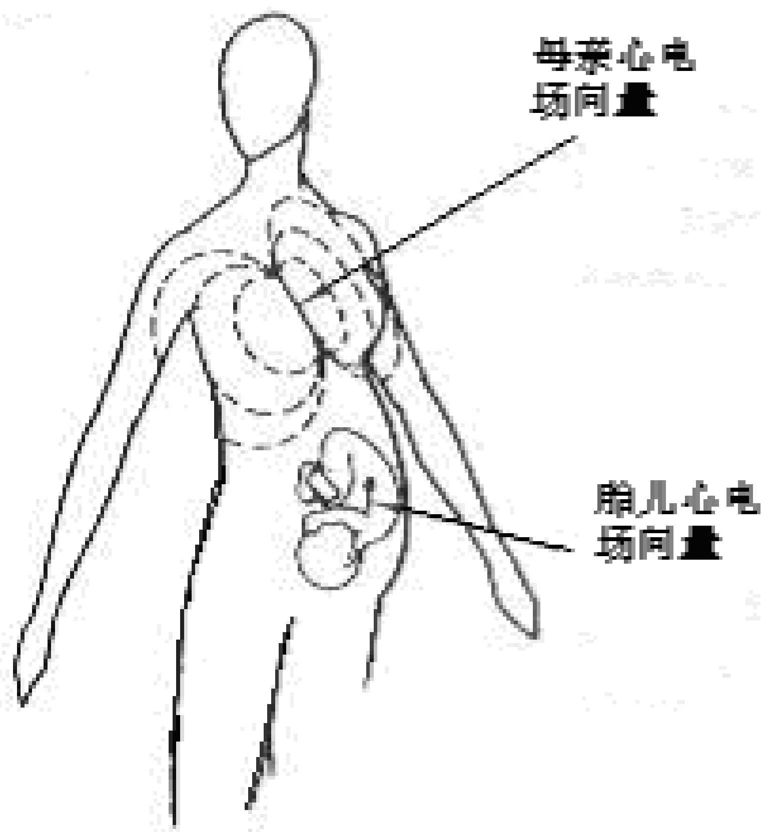
(1) Abdominal ECG are contaminated with background noise due to muscular activity and fetal motion.

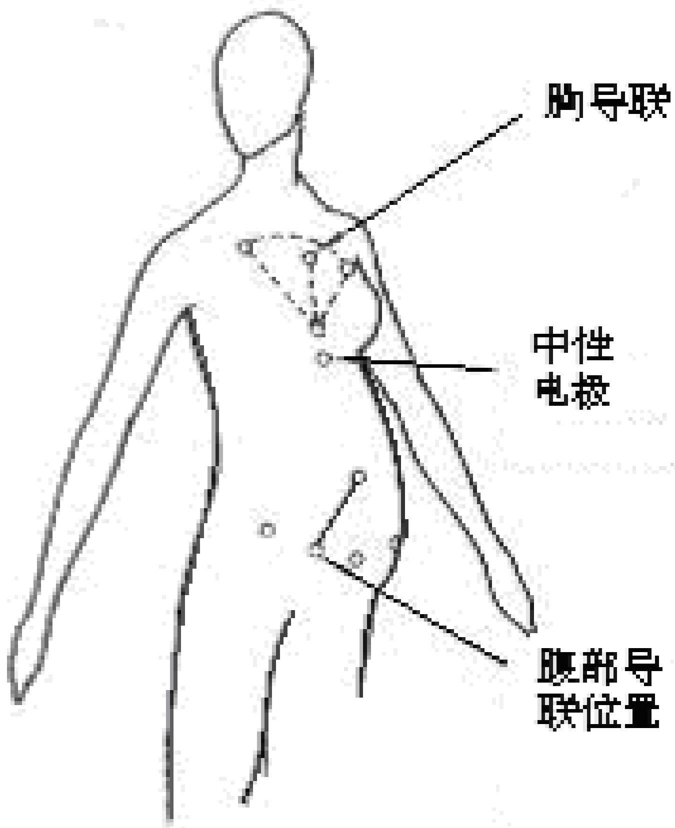
(2) The fetal heartbeat is obscured by the mother’s heartbeat which is about twice as strong.

Method

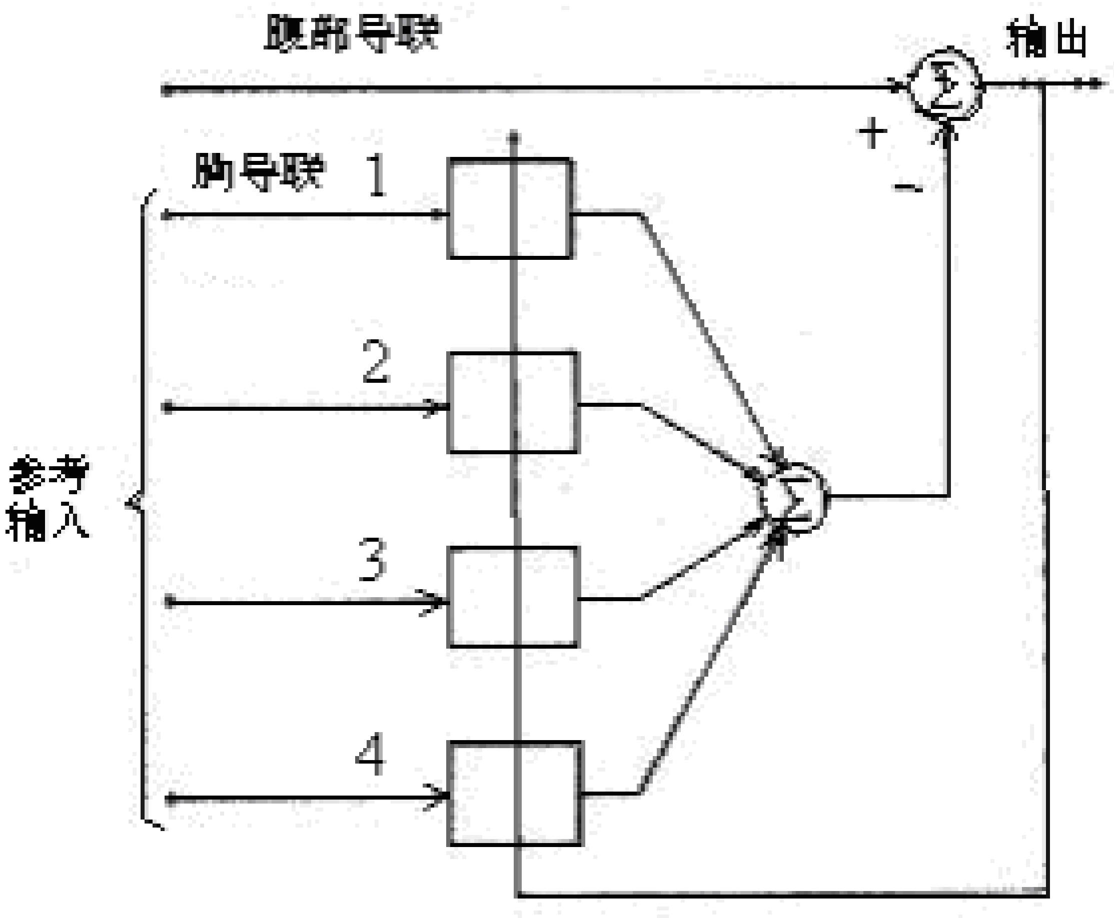
- Using ANC based on LMS algorithm
- main input = Mother's heartbeat + fetal's heartbeat, which is the heartbeat data from mother abdominal.
- Reference input: recording mother's ECG by four electrodes located at mother's chest. Adaptive Wiener Filter was used in this channel.

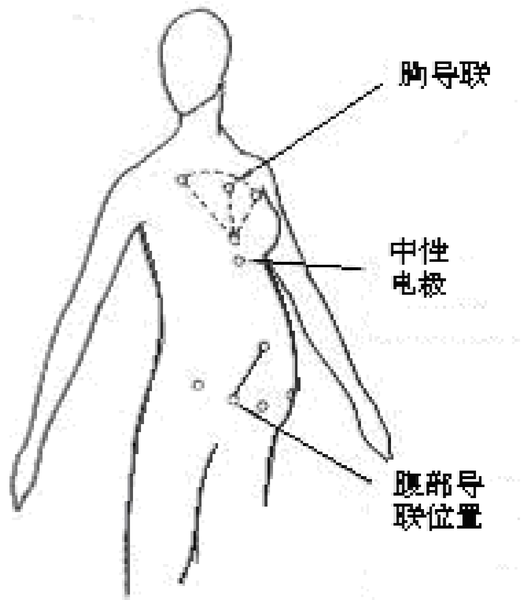
(a) Cardiac electric field vectors of mother and fetus. (b) Placement of leads.



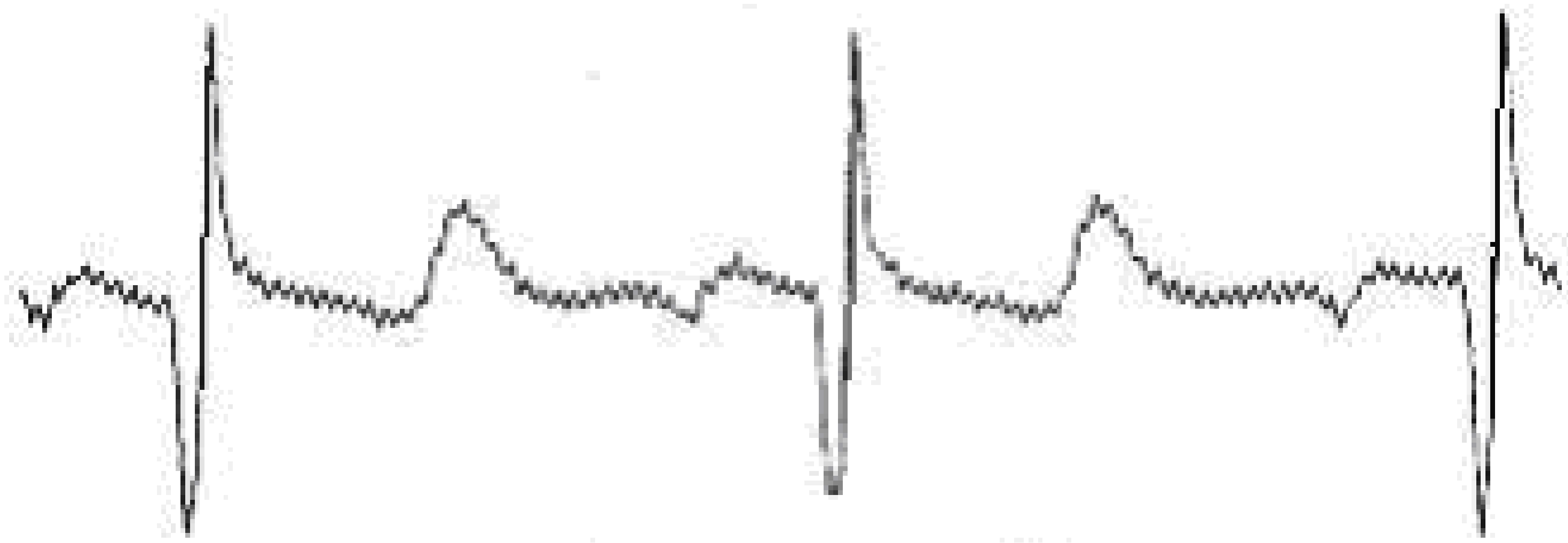


The block-diagram of multiple – reference noise canceler in this study





Experiment 1: Sample rate: 256Hz.
Bandwidth: 3-35Hz



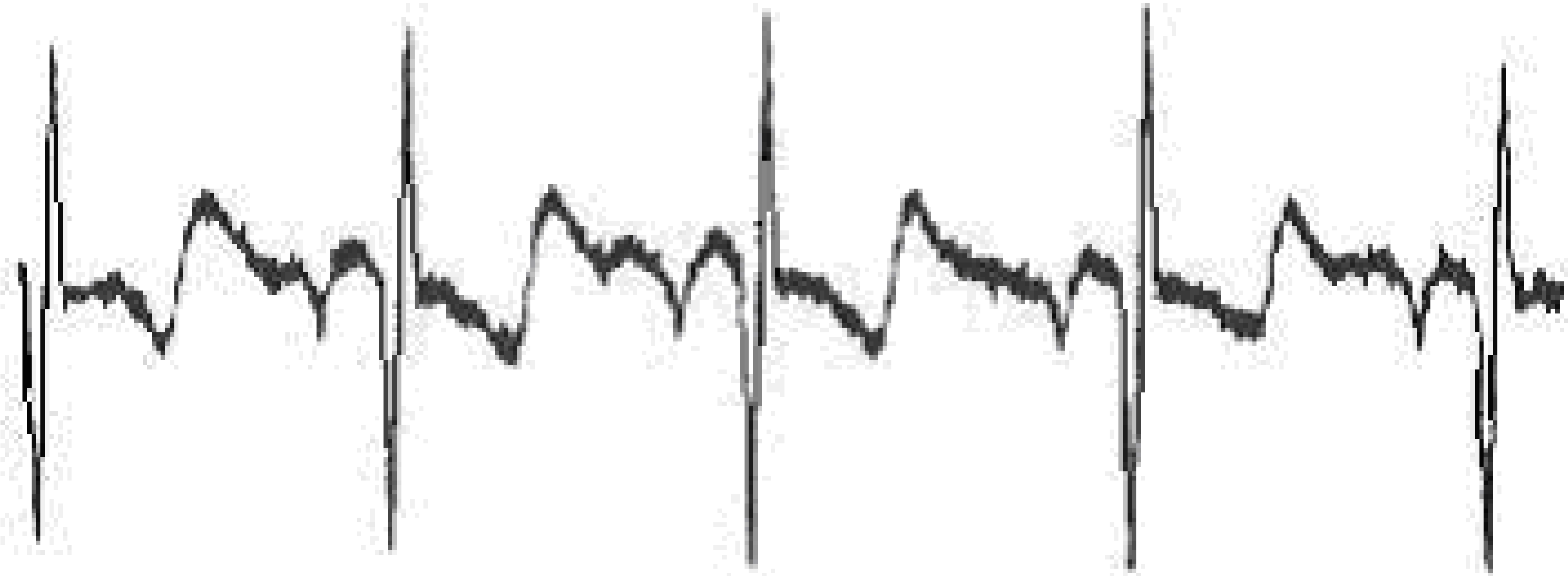
One of reference inputs (Chest leads)

Primary input (abdominal lead)

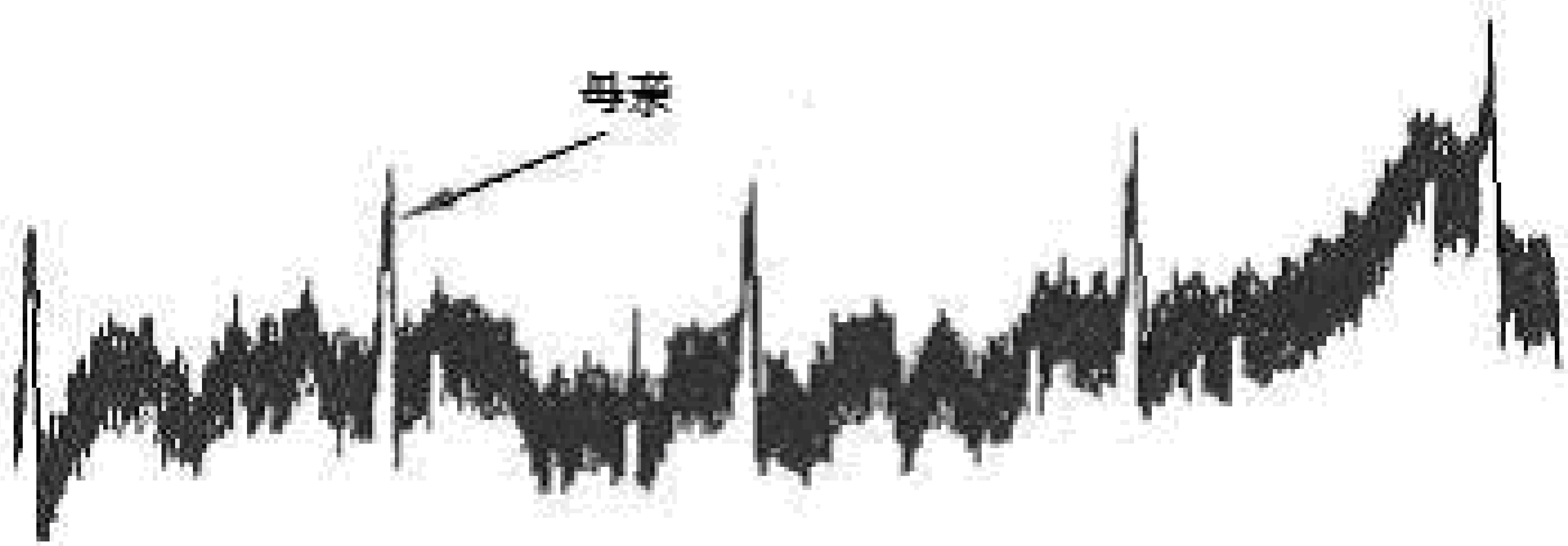
Noise canceler output

Experiment 2: Sampling rate: 512Hz
Bandwidth: 0.3-75Hz

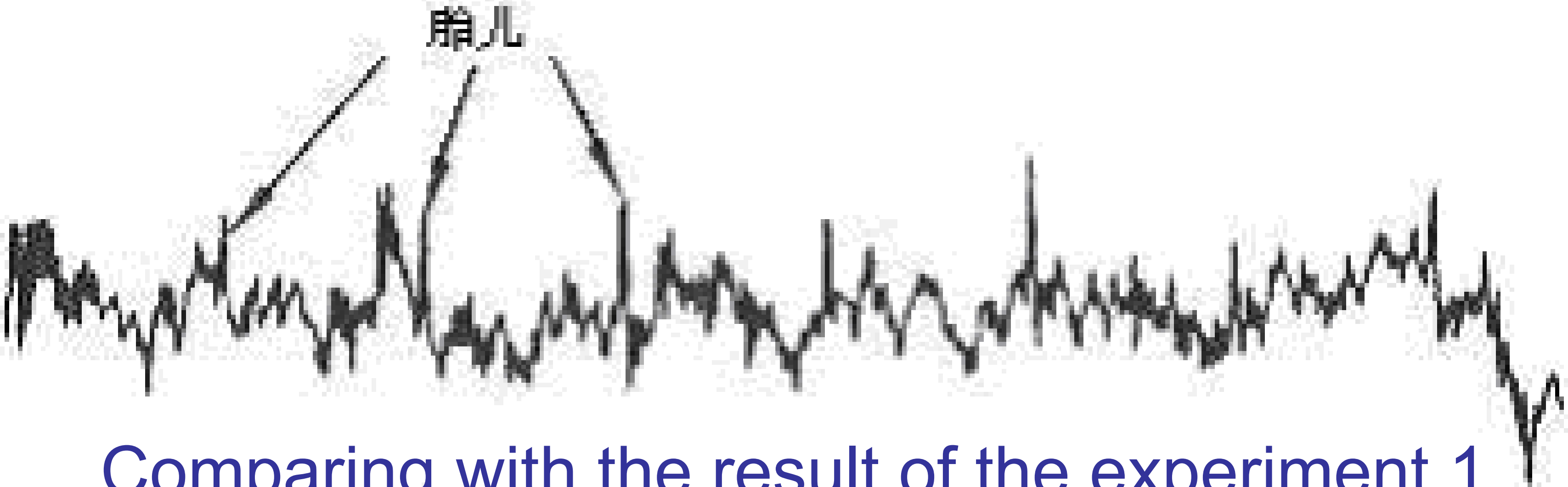
Reference input (Chest lead)



Primary input (abdominal lead)



Noise canceling output



Comparing with the result of the experiment 1

Conclusions

(1) There is strong interference with frequency 60 Hz in main input signal and reference input signal.

(2) ANC is an effective method to enhance the fetal ECG by attenuating the mother's ECG and 60 Hz interference.

3. ANC to enhance Electrogastric Measurements

Clinical problems：

- Electrogastric activities (EGG) can be recorded either intrluminally or cutaneously by electrogastrography.

- The cutaneous gastric measurement is noninvasive. There is needs for clinical diagnosos.

3. ANC to enhance Electrogastric Measurements

- Analyzing the background noise for EGG (0.05-0.4Hz)

(1) The respiratory artifact (0.2-0.4Hz).

(2) ECG (1Hz), which is easy to be filtered because its frequency is much higher than that of EGG.

(3) background noise due to motion, and distortion at the interface of electrode and skin.

3. ANC to enhance Electrogastric Measurements

- **The existing methods:**

In order to enhance EGG, using signal processing technology, such as band-pass filtering, phase-lock filtering, autoregressive modeling，

and adaptive filtering.

EGG measurement

The distance between two adjacent electrodes: 3cm

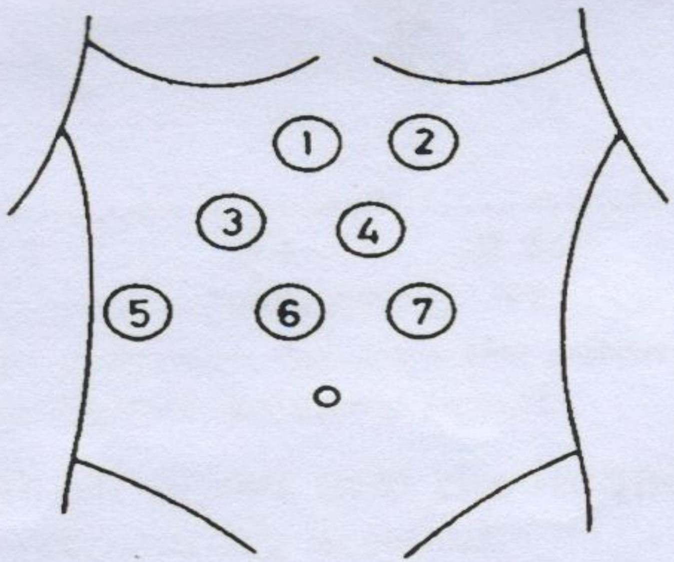


Fig. 1 *Positions of electrodes on the abdomen*

Measurements of electrogastric signals and respiratory signal

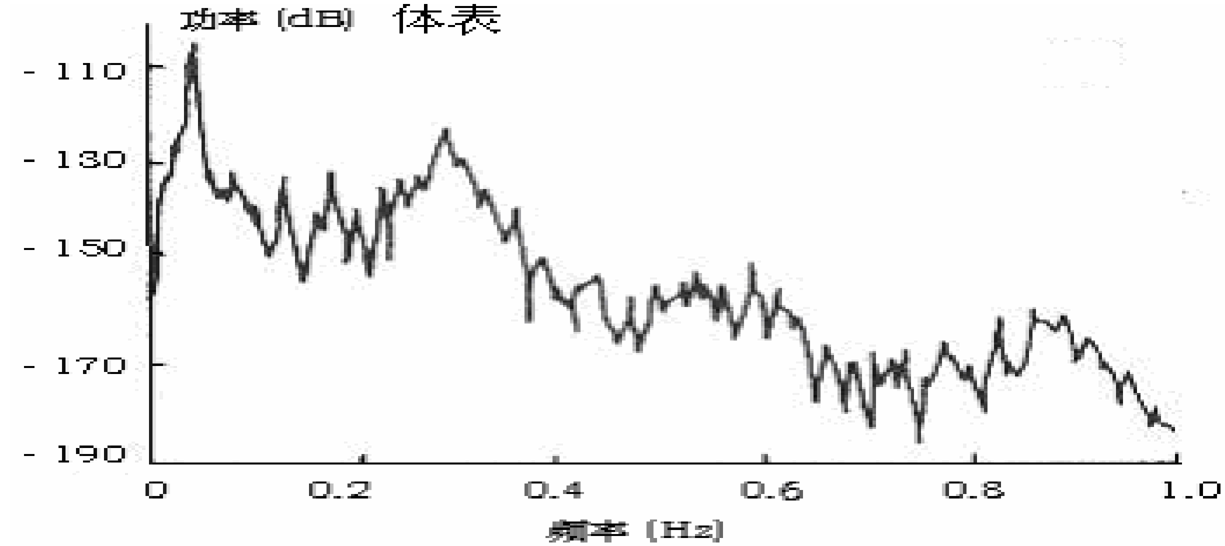
（a） 双极体表胃电信号

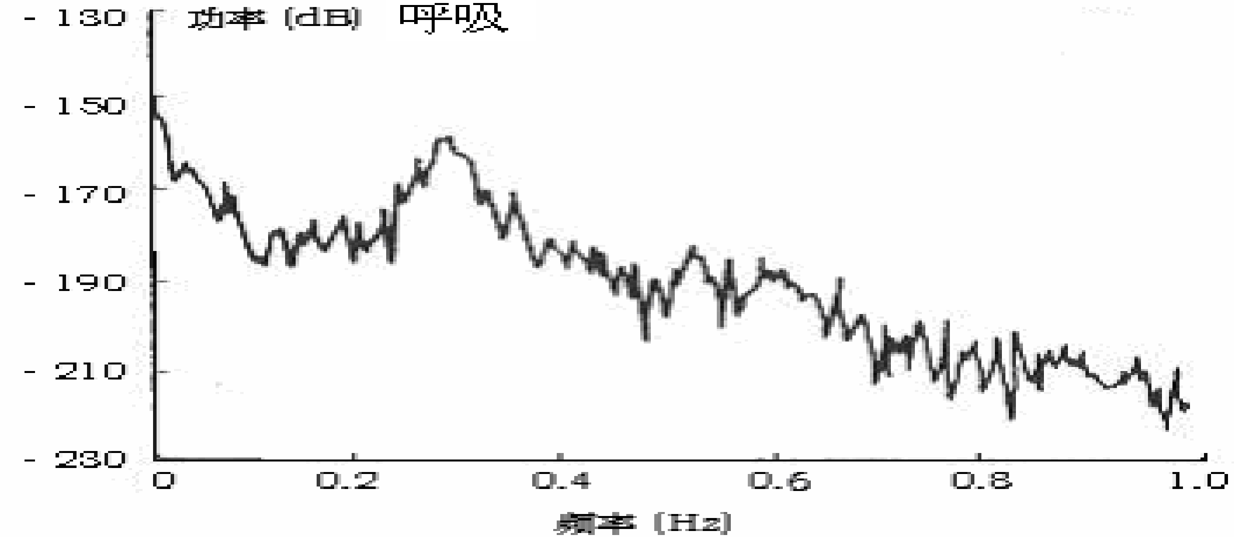
（b）双极体内胃电信号

（c）参考呼吸信号

The respiratory artifact（slow wave) and ECG signals (superimposed spike-like components) contaminated the cutaneous signal.

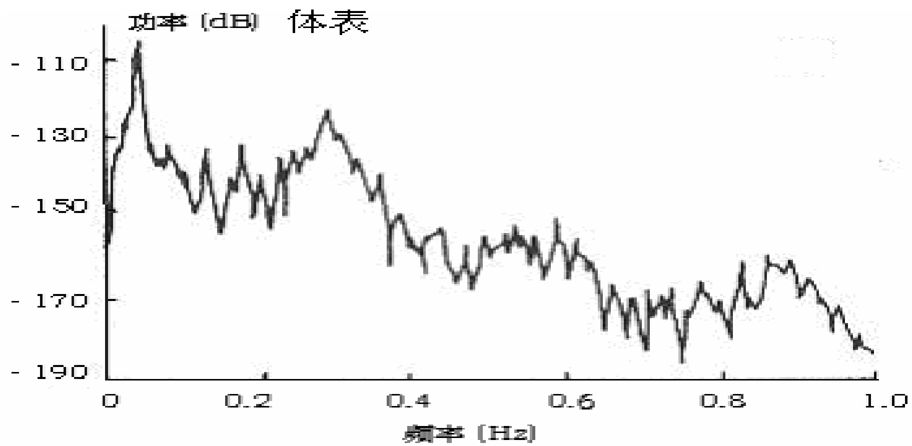
Power spectra analysis
(1) cutaneous gastric signal
(2) respiratory signal

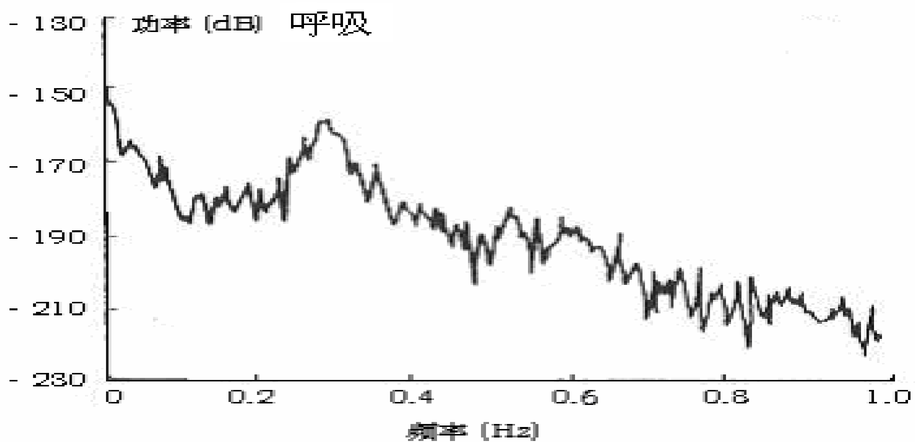




Power spectra result analysis

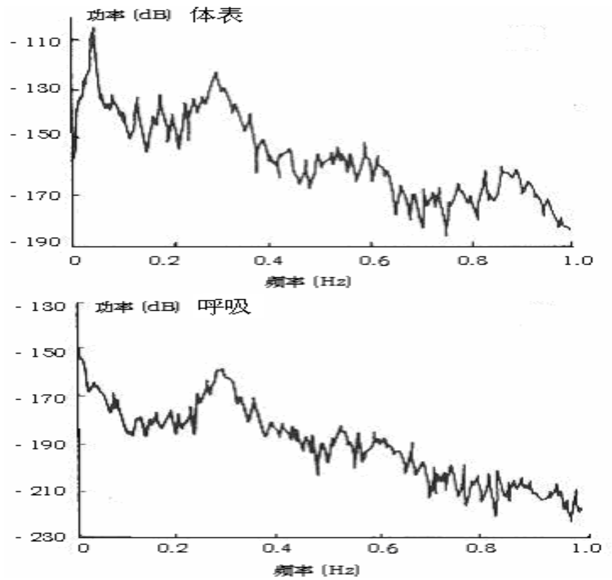
- The PSD of respiratory
- signal shows the
- dominant peak around
- 0.3 Hz.
- The PSD of the
- cutaneous signal shows
- two dominant peaks,
- 0.05Hz due to the gastric
- activity, and 0.3 Hz due
- to the respiratory artifacts



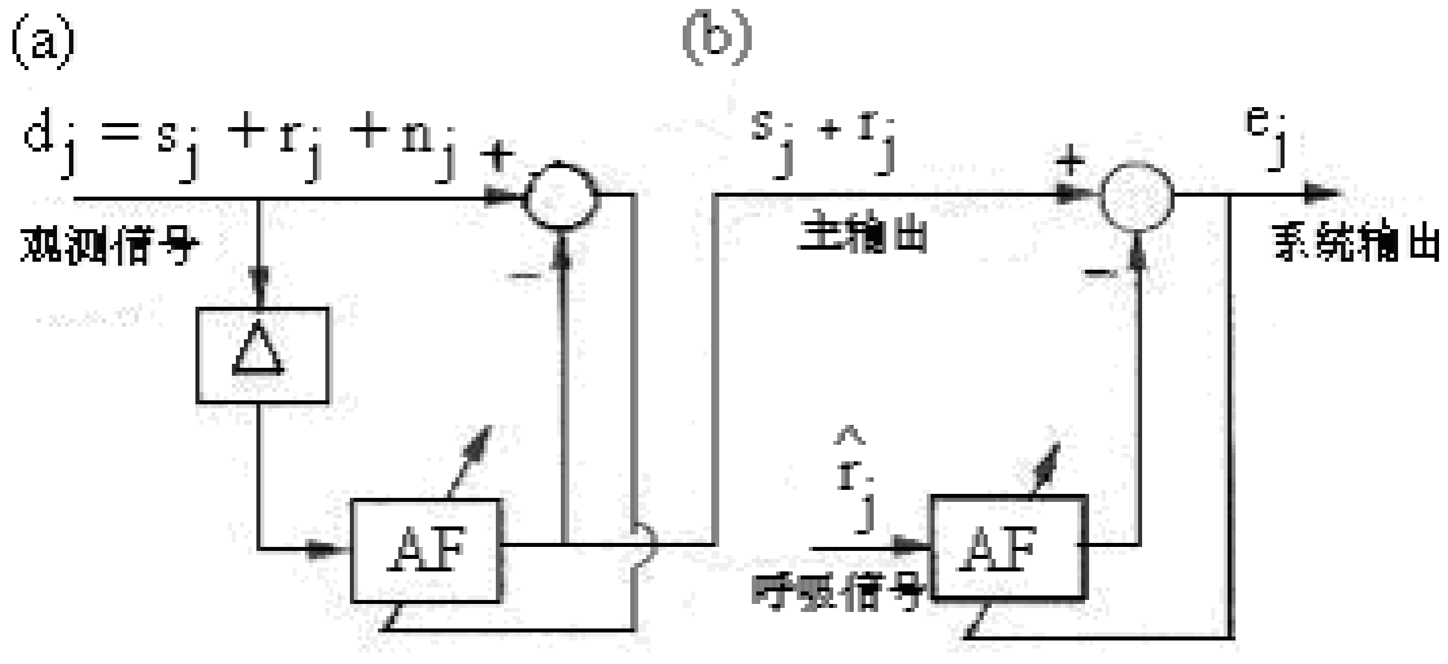


Power spectra result analysis

- The frequencies of respiratory artifacts may indeed overlap the frequency of the real gastric signal, especially for the abnormal activities of the stomach.
- The conventional power spectral estimations failed to separate these two signals.



Adaptive system for cancellation of respiratory artifact and random noise



（a）Adaptive line enhancer stage(ALN)；

(b) Adaptive noise canceler stage(ANC).

Principle

ALN function: elimiate the background noise, n_j, ALE output $s_j + r_j$

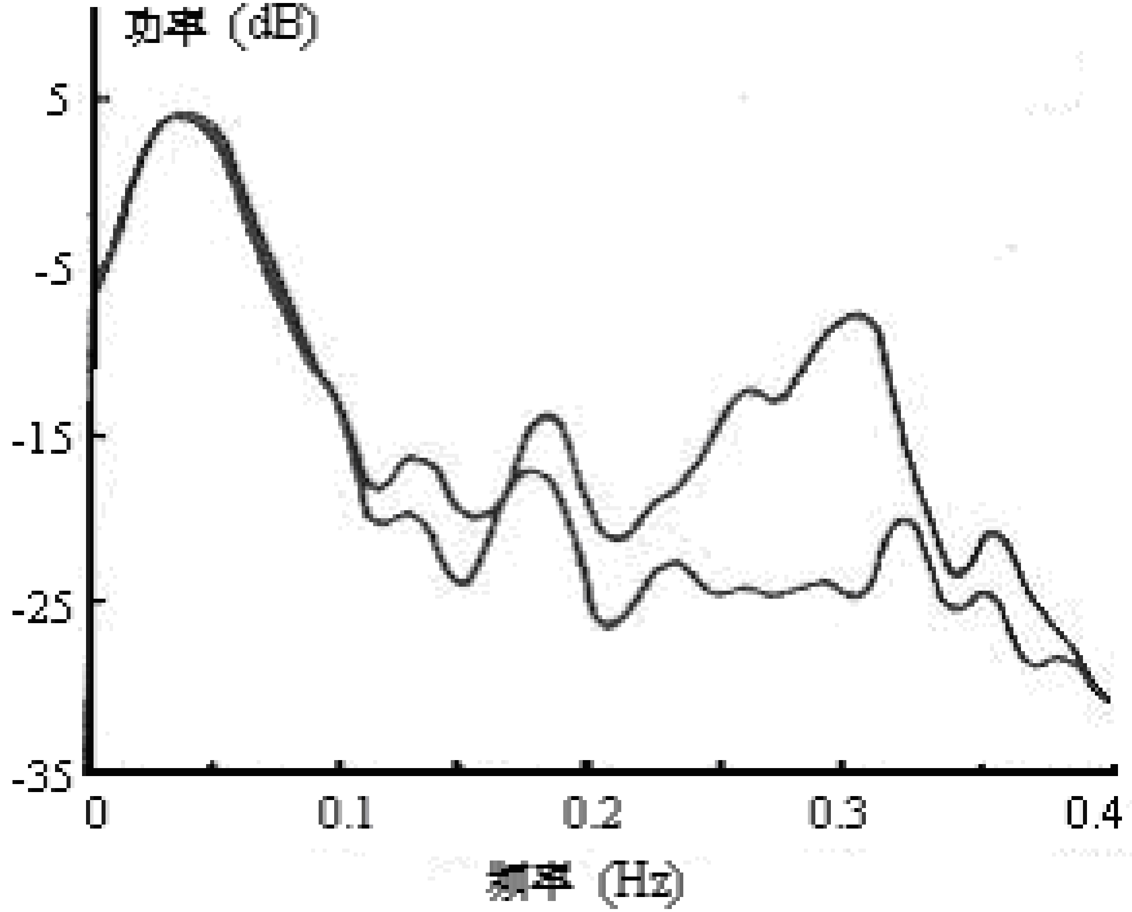
In fact, ALN is a preprocessing unit of ANC

ANC elimiates r_j.

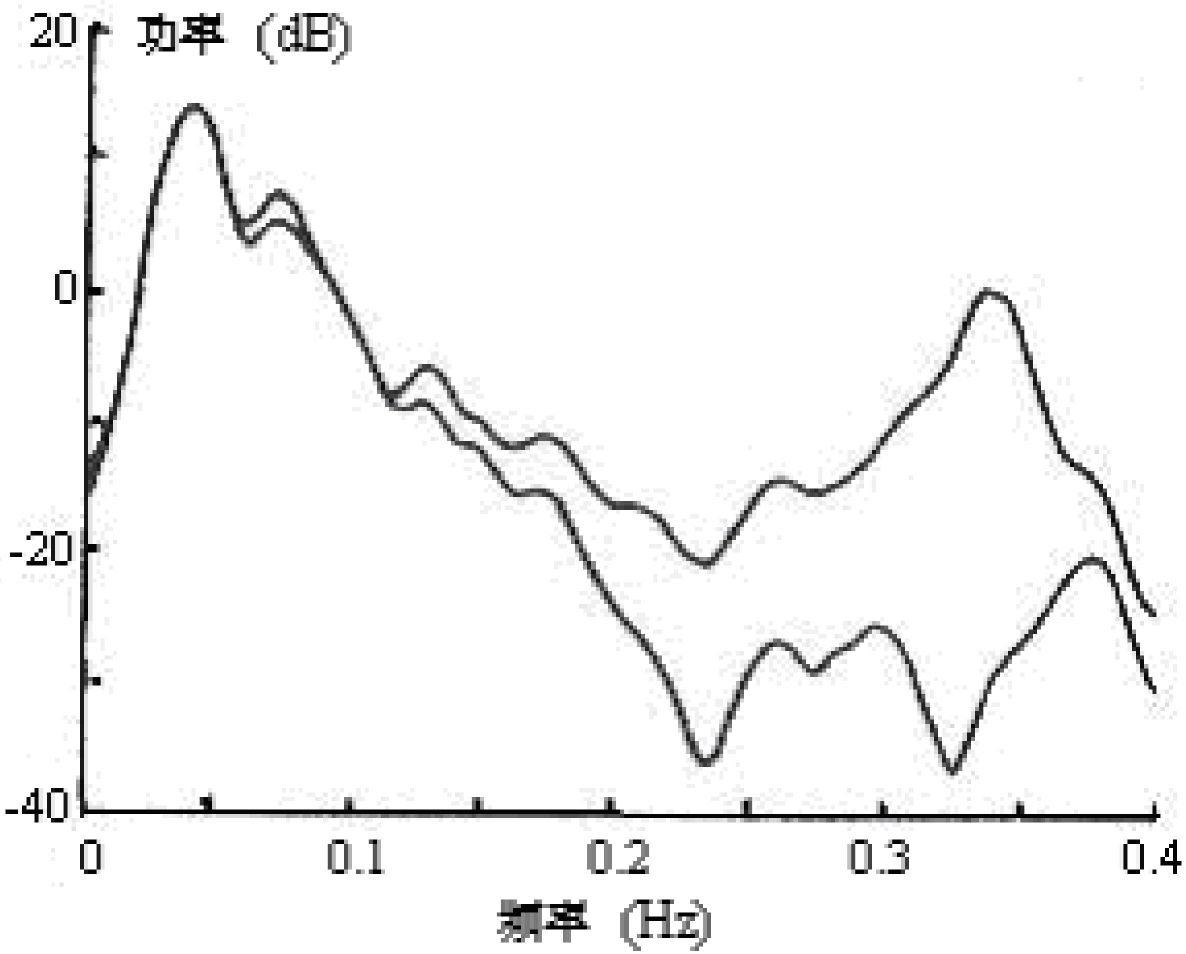
Experimental data

- The periods of EGG and respiratory signals were 40 and 8 samples, respectively.
- ALE filter weight number (Filter order） is 50.
- ANC filter weight number is 10.
- For ALE and ANC, the convergence factor, μ were chosen as 0.01 and 0.05 times the input signal power.
- The main signal d_j was lowpass filtered with a cutoff of 1Hz before adaptive filtering for canceling ECG.

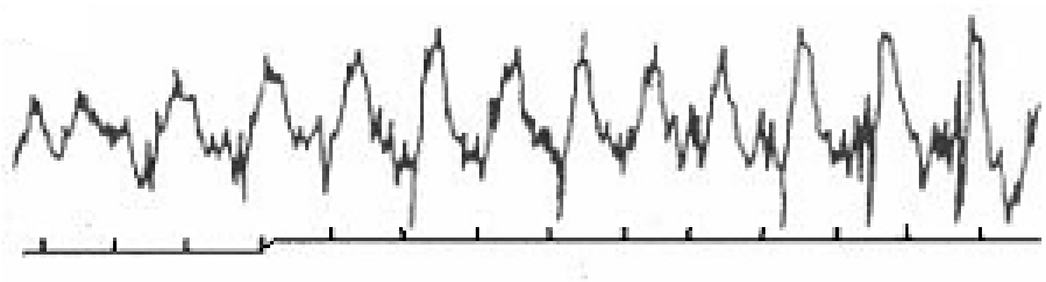
Power spectra of the input cutaneous gastric signal (upper line) and the respiratory artifact canceled output (lower line)



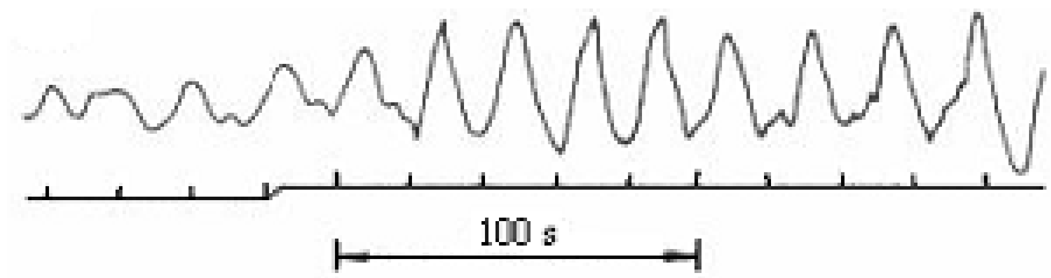
Power spectra of input intraluminal gastric signal (upper line) and the respiratory artifact canceled output (lower line)



The input and output results of intraluminal gastric signal (time domain)



(a) 输入信号



(b) 输出信号

(a) Input signal; (b) output signal

Conclusions

- The adaptive system was able to eliminate the respiratory artifact (between o.25 and 0.4 Hz)
- The signals were preprocessed using a lowpass filter and the ALN.
- A sufficient number of filter weights of ALN and the ANC was chosen so that the entire period of the desired signal could be taken into account.

讨 论

（**1**）关于自适应维纳滤波及自适应噪声对消/自适应谱线增强方法，还有哪些环节你感觉比较模糊，没有搞清楚？

（**2**）从三个应用案例中，你收获了哪些重要知识？

（**3**）若干扰信号与有用信号频带重叠，可以采用哪些方法消除干扰信号？

（**4**）随机噪声有哪些消除方法？

（**5**）其他需要讨论的问题。