Chapter 10

Digital analysis and treatment for electromagnetic disturbances in biomedical instrumentation

Javier Enrique Gonzalez Barajas, Davis Montenegro

Universidad Santo Tomás, Colombia.

javiergonzalezb@usantotomas.edu.co, davismontenegro@usantotomas.edu.co

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1. What is a measurement's network?

The control and monitoring systems to ensure that a process can be performed successfully have become more complex in the last decades, due the inclusion of nonlinear variables; their complexity tends to be increased. All those systems have a highly dependency of feedback signals to increase his reliability, which are acquired by using different types of sensors distributed within the system to simplify the system complexity (Kopetz, 2011), transforming it into information for the control/monitoring system and to deliver useful information about the system status to the user (Kezunovic, Vittal, Meliopoulos & Mount, 2012).

The distributed measurements built a network of measurements (MeN) (Song, Qiu & Zhang, 2011; Pin-Hsuan, 2011), which consist in a group of measurements distributed within the observed system, to describe the possible functional status associated to it against the time. This kind of MeN can be found in biomedical applications (Khalili & Moradi, 2009; Young, 2009), power system analysis applications (Baran & McDermott, 2009), development of high performance communication systems (De Grande, Boukerche & Ramadan (2011), among others.

For example, to measure electrocardiographic signals it is necessary to take measurements at different parts of the patient's body; this way it will be possible, based in the combination of the acquired signals, infer which is the health status of the patient and if he needs some kind of special care due to the results of the study. The implementation of the mentioned example is shown in Figure 1.

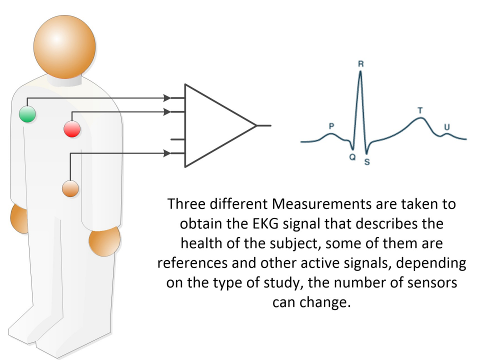

Figure 1. Example of MeN in a biological system

Each measurement within the MeN has to be characterized and correlated with the other also characterized measurements; this way, the set of measurements built a base to determinate the functional states of the observed system.

Additionally to the desired measurements, there are other non-desired components that must be removed or at least considered to handle them and improve the instrument behavior. This chapter presents the generalized techniques to characterize the instrument individually, then how the MeN are built for linear and nonlinear systems. As third part, the digital signal processing (DSP) techniques for removing undesired disturbances is presented, making emphasis in biological signals, which are highly sensitive to different types of disturbances due to his magnitude and wideband.

1.1. Modeling a single instrument

A single instrument can be described as the combination of a data carrier signal with errors signals, the error signals presents different characteristics and can be modeled taking into account the static and dynamic characteristics of the measurement system (Bentley, 2005).

The general diagram to describe the structure of an instrument is shown in the Figure 2. In this structure is possible to visualize that an instrument is the result of different components and each component incorporates dynamic and static error components.

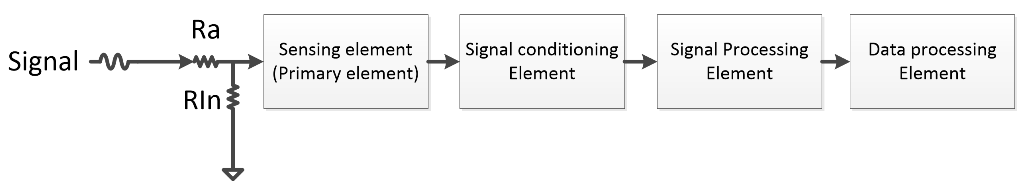

Figure 2. General structure of an instrument

It is also possible to observe that there are digital and analog components within the instrument model, the first one and more important analog component is the input impedance of the instrument (Rin), which depending on the type of signal (voltage or current), must have a value adequate to interact with the source of the signal; this is, for voltage signals the value of Rin must tend to a high impedance value, while for current signals his value must tend to zero. The losses associated to this first stage can be calculated with the following expression:

$$Loss(\%)=\left(1-\frac{Rin}{Rin+Ra}\right)*100 \tag{1}$$

The Equation 1 presents an expression to calculate the losses due the input impedance of the measurement system and the output impedance, generated by the direct or indirect contact between the primary element (sensor) and the measurement point, which can be separated by a dielectric component like air, the skin of a patient, etc.

But when the magnitude oscillates, this is changes of his magnitude against the time; some additional consideration has to be taken into account like the parasite capacitances present at the instrument input. This capacitances works like an analog filter for specific frequencies sending his spectral components to zero, changing the original spectrum of the measured signal and sometimes, reducing the amount of representative information in the acquired data. The complete model is shown in Figure 3.

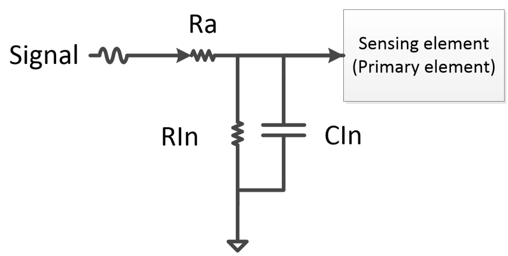

Figure 3. Complete model for the instrument impedance

With the proposed configuration the new equation to describe the losses due the input impedance of the circuit are described by the following expression:

$$Loss(\%) = 1 - \left| \frac{\frac{Rin}{j\omega C}}{\frac{Ri\,n}{j\omega C} + \left(Rin + \frac{1}{j\omega C} \right) Ra} \right| * 100 \tag{2}$$

Where ωC is the term to determinate which components of the input spectrum are going to be affected by the value of C, a characteristic that can be treated by using another parallel capacitances ($\omega = 2\pi f$) or adding other configurations with LC or RL components.

Inside the instrument, the different stages described in Figure 2 has associated two types of errors: the systematic error and the random error (Dunn, 2005; Webster & Eren, 2013); the first one can be treated because it can be modeled and minimized using mathematical methodologies, but the second one, because of his random behavior, can only be associated to a probability distribution function where the standard deviation is defined by the manufacturing process and materials, and can be identified by the class index of the element.

This way, each part of the instrument can be described as follows:

$$Signal(t) = f(t) + Es + Ea(t) \tag{3}$$

Where f(t) is the acquired signal after input impedance, Es is the systematic error, which many times is associated to the magnitude of the measurement and Ea(t), is the random error. To calculate the total error associated to the measurement system due the presence of the random error, and the low probability that all the elements of the instruments are going to fail at the same magnitude at the same time instant, the following expression can be used:

$$Total\ Error = \sqrt{E_1^{\,2} + E_2^{\,2} + E_3^{\,2} \ldots + E_n^{\,2}} \tag{4}$$

Where E_n are the errors (class index) associated to each component of the instrument. This is because the systematic error can be corrected by the user after a calibration procedure in site; this way the total error can be included in the range of the instrument like an expected variation in the measurement (Ej: 0-85°C ± 1%).

1.2. Modeling a measurement's network

A MeN is a set of measurements to describe the system functional state, there are many applications on MeN oriented to describe linear and nonlinear systems. This relationship between the different measurements is made using matrix arrangements, which involves the taken measurements to calculate other variables that can be estimated in the same or other units. One example of this is the hydrostatic tank gauging (HTG) used to determinate the level of a liquid within a closed recipient based in pressure and temperature measurements. The general set of measurements to do this build this model is the following:

$$\begin{bmatrix} 1/h12 & -1/h12 & 0 & 0 \\ 1/Den(z-1) & 0 & -1/Den(Z-1) & 1 \\ 1/At & 0 & -1/At & 0 \end{bmatrix} \begin{bmatrix} P1 \\ P2 \\ Ps \\ hi \end{bmatrix} + e = \begin{bmatrix} Den(z) \\ Level \\ Mass \end{bmatrix} \tag{5}$$

Where *Den(z)* is the density of the liquid at the moment of measurement, *Den(Z-1)* is the density of the liquid at the previous instant of measurement, *At* is the transversal area of the tank, *h12* is the high between the pressure sensors *p1* and *p2*, *e* is the error vector and *hi*, is the high between the bottom of the tank and the sensor *p1*. In this model it is possible to add more measurements like temperature to improve the accuracy of the results.

2. Disturbances modeling

2.1. Disturbances classification

Electrical equipment adds disturbances that affect directly the MeN applied to biomedical instrumentation system; the electrical disturbances are the most common found due the fact that electric power sources are necessary to instrumentation devices work (Chatterjee & Miller, 2010).

2.2. Mathematical models to describe disturbances

If x(t) is a signal acquired by a MeN System, it is composed by a signal under study s(t) and the disturbance signal r(t) (Equation 6).

$$x(t)=s(t)+r(t) \tag{6}$$

In this case, r(t) is a disturbance generated by a power electric system. The Equation 7 shows a basic mathematical model to describe it where A is the signal amplitude and F is his frequency, (60 HZ for american system and 50 Hz for european system) (Kim, Ku, Kim, Kim & Nam (2007).

$$r(t)=A*\cos\quad(2*\pi*F*t) \tag{7}$$

The power system signal can compose by more than one frequency component, a reason for why it is necessary his caracterization in the frequency domain. Figure 4 shows the spectrum of two types of disturbances: constant frequency and variable frequency

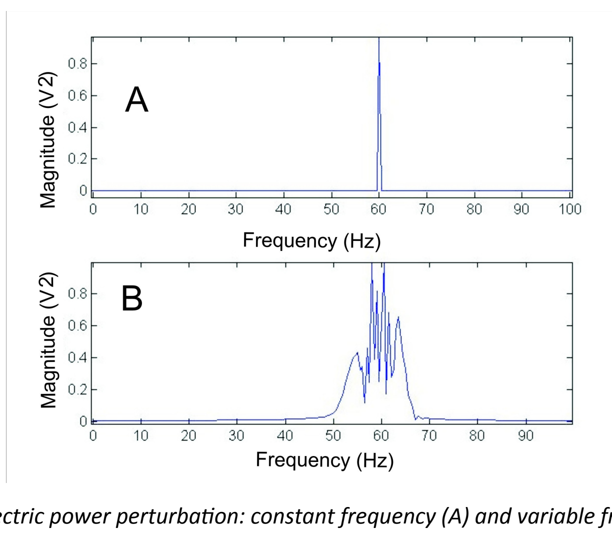

Figure 4. Electric power perturbation: constant frequency (A) and variable frequency (B)

2.3. Detection of disturbances

Through the Fourier Fast Transform (FFT) it is possible to study the addition process between a biomedical signal and the disturbance with variable frequency. In this case, the biomedical signal is a electrocardiographic one. Figure 5 shows the simulation.

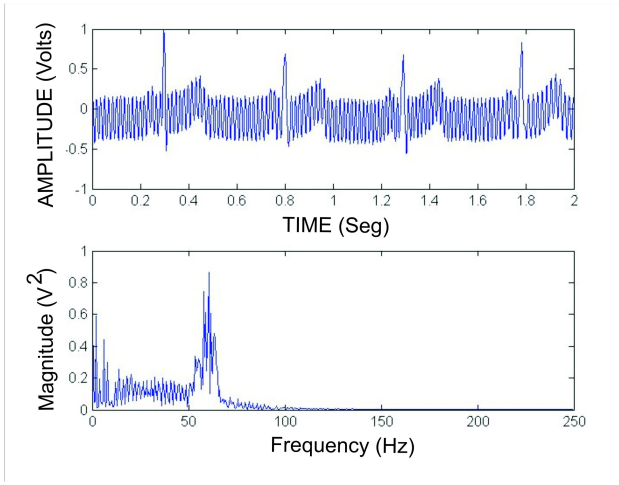

Figure 5. Simulation of addition process between a electrocardiographic signal and a power electrical disturbance

3. Design and implementation of disturbances simulation

The power electrical system has alterations caused by the non-adequate operation of the electrical installations. These alterations must be implemented in the simulation of power electrical disturbances.

3.1. Continuous or discrete time?

The electrical disturbance is a time continuous signal, but it can be simulated using a time discrete signal. It is important to include in the model characteristics like voltage drops, voltage cuts, over voltage and the inclusion of steady state and transient frequency components in the discrete signal.

3.2. Alternatives for implement a simulation

An electrical power perturbation with harmonics components can be simulated using the equation in 8.

$$r(t) = A_0 * \cos(2*\pi*60*t) + A_1 * \cos(2*\pi*180*t) + A_2 * \cos(2*\pi*300*t) \quad (8)$$

The Figure 6 shows the simulation of a biomedical signal distorted by an electrical power signal with harmonic components.

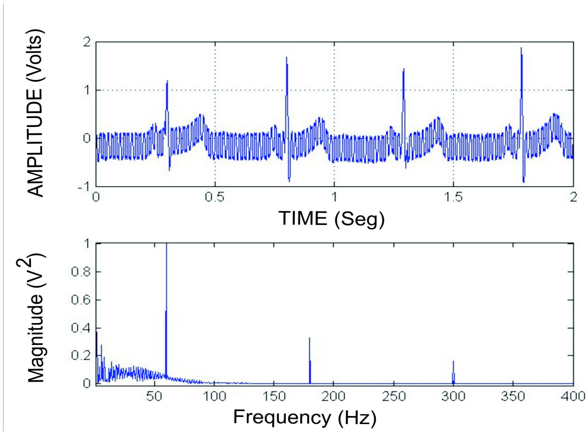

Figure 6. Electrocardiographic signal distorted by an electrical power disturbance based in harmonics components

3.3. The system dynamics and the code to simulate

The simulation of an electric power perturbation using a sampling frequency 500 Hz and 500 samples, can be implemented using Matlab and the following program lines:

```
fs=500;
Ts=1/fs;
N=500;
n=1:N;
t=(n-1)/fs;
r=0.5*sin(2*pi*60*n*Ts);
```

An electric power perturbation with sinusoidal variation of its frequency value:

```
R=0.7*sin(2*pi*0.8*n*Ts)+60;
for n=1:500
r(n)=0.4*sin(2*pi*R(n)*n*Ts);
end
```

An electric power perturbation with harmonics components:

```
fs=1500;
Ts=1/fs;
N=3000;
n=1:N;
t=(n-1)/fs;
r=0.3*sin(2*pi*60*n*Ts) +0.1*sin(2*pi*180*n*Ts)+0.05*sin(2*pi*300*n*Ts);
```

4. Classic methodologies for removing disturbances in measurement networks

A classical solution is a notch filter using the Equation 9. Where *a* depends of the disturbance frequency (60Hz) and the sampling frecuency (Fs) (Equation 10).

$$y(n)=x(n) + a*x(n\text{-}1) + x(n\text{-}2) \tag{9}$$

$$a=-2*\cos\left(\frac{60}{Fs}\right) \tag{10}$$

The notch filter is an effective solution only if the perturbation is composed by a sinusoidal signal with 60 Hz. Figure 7 shows the performance of the notch filter applied to a disturbance with harmonics components.

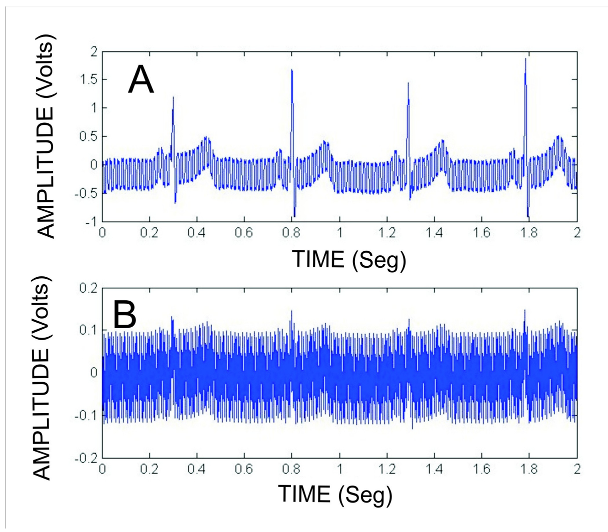

Figure 7. Electrocardiographic signal distorted by an electrical power disturbance with harmonics components (A) and the signal filtered using a notch filter (B)

5. Design and implementation of complete algorithms

An adaptive filter FIR (Figure 8) is composed of an input signal x(n) and output signal y(n). The signal e(n) is calculated using the difference between y(n) and the desired signal d(n).The adaptation ruler uses the coefficients Wk applied to the cancellation of the error signal e(n).

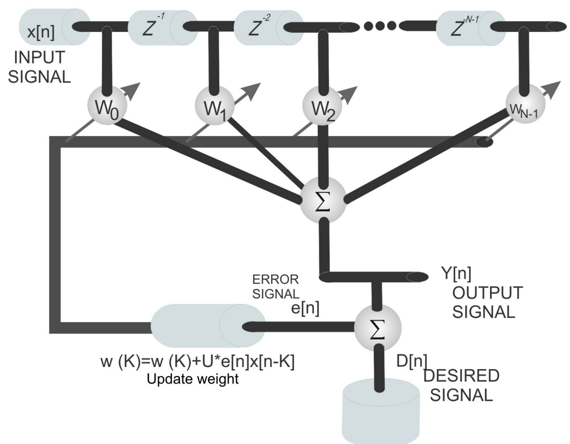

Figure 8. Block diagram of adaptative FIR filter

5.1. The inclusion of digital filters in simulated systems

In Matlab is possible the adaptive FIR filter implementation using the following program lines

```
B=zeros(1,50);
B(1)=1;
L=length(B);
% Cálculo del paso de coeficiente de µ
StepU=1/(2*sum(x.^2));

for n=L+1:N
c=0;
for k=1:L
    c=c+B(k)*x(n-k);
end
y(n)=c;
e(n)=d(n)-y(n);

for k=1:L
B(k)=B(k)+e(n)*StepU*x(n-k);
end

end
```

The coefficients of the adaptive FIR filter can produce a transfer function applied to the electric disturbance attenuation. Figure 9 shows the frequency response of the transfer function applied to disturbance with harmonics components.

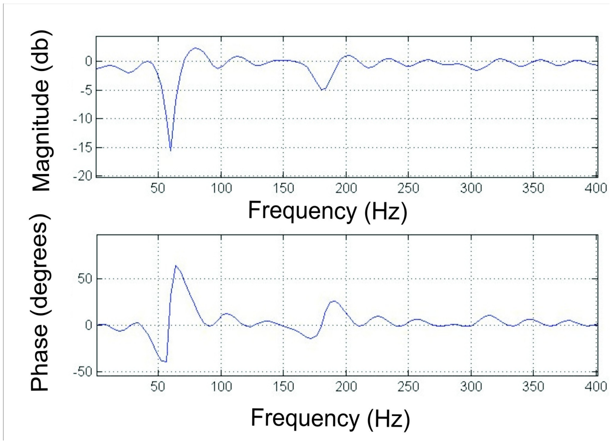

Figure 9. Frequency response of the adaptive FIR filter applied to electric power disturbance with harmonics components

Figure 10 shows the electrocardiographic signal distorted using an electrical power disturbance with harmonics components filtered by an adaptive FIR filter.

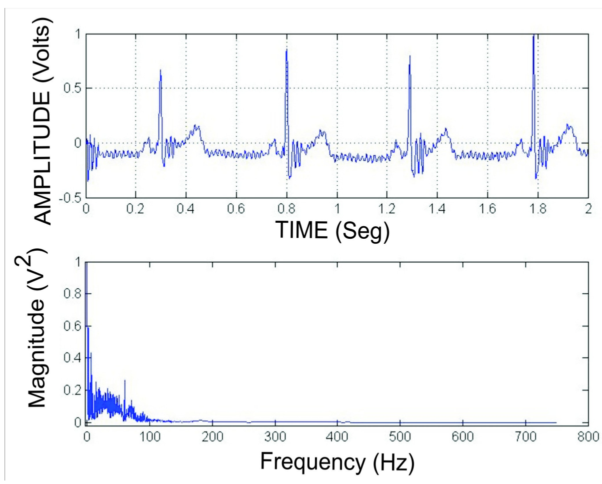

Figure 10. Electrocardiographic signal filtered by an adaptive FIR filter

5.2. The selection of parameters for digital treatment of the disturbances

To implement a system for the treatment of disturbances, it is necessary to have criteria for selecting the parameters of the algorithms.

In the implementation of an adaptive FIR filter is important the selection of the parameter μ. It is the adaptation coefficient (Equation 11).

$$\mu = \frac{1}{2 * \sum_{n=0}^{N-1} |x(n)|^2} \tag{11}$$

6. Conclusions

It has been presented a case of application where the different signal components within a biomedical instrumentation are digitally treated, due the presence of different types of errors and sources, it is necessary to use multiple methods to minimize them.

The MeN represents a complex system that allows improving the performance of an instrumentation system, but it is necessary to consider that multiple errors and disturbances are involved in this complex system to achieve the expected results.

The biomedical instrumentation needs sensor networks applied to electrophysiological signal acquisition. The electrophysiological signal can be distorted by disturbances originated in the electrical system. This chapter tried models and methodologies to simulate the distortions and the strategies to mitigate the influence in biomedical sensors systems.

7. References

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