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Some Fundamentals And Concepts For The Design, Evaluation And Comparison Of Algorithms In Biosignal Processing.

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ABSTRACT

This article is aimed at students to acquire skills in the analysis of biological systems which are complicated systems to treat. Analyzing these systems is usually a difficult task because of the complexity and the electronic engineering student must have a real ability to understand them based on the knowledge previously acquired in the different courses previously advanced. Often the analysis is carried out live, which means that the specific system under test cannot be isolated from another system that interferes with it. Very often the inputs and /or outputs of the system are difficult to access. These fundamentals and concepts well understood by students should serve as a tool for their development as engineers in the field of biomedical instrumentation. The student will venture into the management of this tool to elaborate the analysis of these systems such as the processing of biosignals. Sophisticated signal processing algorithms are used for the direct and indirect study of the performance of biological systems under many necessary measurements. Such algorithms are required to incorporate into monitoring, protection and diagnostic instruments, among others.

Keywords: Algorithms, Biosignals, Diseño

I. INTRODUCTION

Databases are a basic and required infrastructure for the development of algorithms for signal processing which are required for the design, evaluation and comparison of algorithms. A good database should be provided with sufficient examples of the variety of signal types and the population they represent. Acquisition conditions must be extremely careful and it is expected that signal databases can become standards, which allows to meet the objective evaluation and comparison of performance. This is how some databases have been standardized and among which are the following:

a) MIT Arrhythmia Database.
b) AHA ventricular arrhythmia assessment database.
c) European ST-T database providing a collection of ECG recordings showing ST transients and T-wave changes.
d) Physionet database.

These databases are generally created to solve specific questions or verify hypotheses formulated, which determines the number of signals to be acquired, the sampling rat to which they will be acquired, the protocols under which the acquisition of the signals will be carried out. However, by having a certain number of signals in a database, you can also solve other types of issues that were not initially intended, but usually require more signal acquisition for specific applications.

As biomedical databases are used for scientific and reference purposes, we seek to have the best possible signal quality. Taking into account that the signals of the databases are obtained in laboratories and different sites, the signal recording conditions must be harmonized to guarantee the quality of the signals, in addition, care must also be taken with the periods of data collection in different sites. The recording of biomedical signals does not in principle have the objective of creating a database. Officially, it only seeks to monitor or diagnose the patient or do research. Recorded signals are important in themselves, as only through the evaluation of them can the meaning of specific signal models be understood and such signals can become the key to future signal analysis and processing.

2. DATA ACQUISITION

Normally, surface records of body electrical activity are obtained in the form of potential differences between an active electrode and a reference electrode (ideally inactive), as a function of time; this results in a set of signals collected at different points depending on what is being measured. From the whole, it is about establishing spatial or temporal relationships of different structures that contribute to the production of a spontaneous or provoked phenomenon. The first problem encountered is the selection of a configuration or assembly of electrodes that allows adequate spatial sampling, depending on the type of response under study, along with the selection of the reference to be used.
The selection of the assembly and the number of electrodes depending on the application results from a balance between theoretical and practical considerations. The number of electrodes must be high for interpolation to be meaningful, while a user-friendly number of electrodes must be maintained. Otherwise, the time required for the location of the electrodes is high and it is difficult to preserve the conditions required for the signal recordings.

In the recording of phenomena that present a local activity, it is important that an electrode is close to the point of maximum amplitude of the electric field; the electrodes found in the adjoining regions record potentials of much smaller amplitudes. This means that with respect to the points where the signal originates, a greater number of electrodes must be placed or relocated.

In relation to the distance between electrodes that pick-up EEG signals, Nyquist's principle can be applied to the problem of spatial sampling. The separation necessary for a good evaluation of electrical accidents for somatosensory evoked potentials (PES) is estimated. The study aims to sample the cortical region that is considered responsible for the main components of PES. Subsequently, a spectral analysis is performed by means of the Fourier transform, and in this way the maximum number of spatial frequencies is determined. Finally, the distance between the electrodes is stipulated, by means of the expression: $1/(2*F_{max})$. This distance corresponds to 3 cm. The same method can be applied to assess this distance for other brain-generated potentials.

The cartographic representation requires the use of a common reference, which must be theoretically inactive. The information recorded about an electrode comes from the underlying structures. Now, each channel corresponds to what is called a shunt, which is the potential difference between the two registration points, that is, between the recording electrode (or active electrode) and the reference electrode. For this reason it is desirable that the reference electrode is at zero potential. It is important to note that the use of an electrode assembly, even in a referential configuration, has the effect of a spatial filter that amplifies the importance of certain regions to the detriment of others. There are multiple solutions for the selection of the reference, but none is free of drawbacks, for example, in the case of EEG signals there are:

a) Average reference of type Wilson.
b) Reference of interconnected ears.
c) Reference chin or nose.
d) External-vertebro-clavicular reference.
e) Necklace reference.

Biomedical data can be collected using a variety of methods to interface with the hardware including acquisition cards inserted into the PC bus or ports: serial (RS232), USB, among others. Data can also be generated within the computer in the form of questionnaire responses or automation of activities using intelligent agents, giving specific functionality to apparent applications.

3. CONDITIONS FOR THE ACQUISITION OF SIGNALS

The acquisition of pure physiological signals is highly dependent on amplification and filtering, factors that greatly affect the signal-to-noise ratio of the information obtained. Despite the similar scenes, the signals recorded on different devices are different, due to the implementation of sensors, amplifiers and filters. The signal-to-noise ratio in low-voltage signals is especially sensitive to the implementation of amplifiers of a CMRR greater than 80 dB.

As the channels of different signals are interpreted as close, synchronization between signals is very important and must be taken into account when choosing the recording equipment. Synchronization between signals begins to be a significant problem when different data is recorded using different devices with different clocks for each different data file, this is the case of the usual scenario in intensive care where several equipment record signals in parallel. It must be ensured that the start time of the machines is the same and that there is no difference in the clock rats of the equipment, which must be chosen so that the requirements for subsequent analyses are met.

4. SIGNAL PROCESSING

The almost permanent presence of overlapping noise in recorded biopotential signals, generally due to electromagnetic interference, motion artifacts or the characteristics of the electrolyte electrode interface, has led to various methods of signal enhancement. Usually, high pass filters are implemented to eliminate basic trends and low pass filters to eliminate noise, obviously this is the application of a band pass filter that will have specific cut frequencies depending on the type of signal to be processed. In many algorithms the filters pass high and pass low are implemented separately and in others only the high pass filter is implemented, in addition, most algorithms implement rules to reduce the detection of false positives. Currently there are several types of algorithms for obtaining a clean biomedical signal:

- Algorithms based on derivatives: In such algorithms the filters pass high are implemented as differentiators, there are algorithms that work only with the first derivative, or with the second, or with linear combinations of the magnitudes of the first and second derivatives.
- Algorithms based on digital filters: several types are found:

  - Algorithms are proposed where the signals are filtered by two filters pass low in parallel with different cut frequencies and the difference between the outputs of the filters is the signal passes expected band y1(t), which is then processed by:

  - The signal that is finally obtained is y2(n) + the filter output signal passes low with the highest cut-off frequency.

  - Another type of algorithm of this type is basically a combination of multiplications between the values of the magnitudes of the derivatives. Another type of algorithm that is used is one in which the signal initially passes through a band pass and then is differentiated, the resulting signal is computed by average of the output of the differentiator; the filters pass band and differentiator use coefficients that are particularly convenient for an implementation on processors with short word length, for the detection of peaks, a variable v is introduced that contains the value of the most recent maximums, the characteristic peaks of the signal are obtained by comparison with the variable v.

  - An algorithm similar to the previous one is proposed, only that it uses different filters, the signal is divided into 15 points, the maximum of each segment is compared with adaptive noise and peak levels, to estimate and classify depending on the distance to each of the estimates.

- Algorithms are also proposed that are based on neural networks, in which the signal is filtered by two filters passes different bands and then the output of these is multiplied.

Most filters used in biomedical instrumentation have linear phase response and are highly computationally efficient.

Other methods used to obtain relatively clean biomedical signals are:

- **Wavelet Transform Method (WT)**
  Here a filter bank is used, where the coefficients of the filters are derived directly from the discrete wavelet function, since the input signal will be sampled. The method of detection of peaks mentioned in this section is based on the detection and classification of singularities using the coefficients of the wavelet signal, then the correspondence of singularities between the input signal and its wavelet coefficients, the classification of peaks is accompanied by the computation of degrees of singularity.

- **Methods related to the wavelet transform:**
  The wavelet transform is also used for signal classification, in addition, the possibility of data compression by the threshold of wavelet coefficients has been demonstrated.

- **FILTER BANKS Method (FB)**
  This method uses the decomposition of the signal into sub-frequency bands and processes them into these sub-bands before recomposing it. It takes into account the specific energy distributions of the signal in the frequency domain.

  A wide variety of algorithms have been developed to perform certain processes, such as signal enhancement and detection of characteristic parameters. The algorithms for each of these activities represent unique solutions, without ignoring the benefit of other tasks. Each algorithm requires a different group of processing filters, which are not common to other processing tasks.

  The conformation of the Filter Bank (FB) allows multiple tasks of processing a signal, which are executed by a specific group of filters. In addition, each of these simultaneous tasks can be performed at lower sampling rates than the original signal acquisition rates under study.

  A filter bank is simply a set of low-pass, high-pass, and through-pass filters, each of which covers a band in the frequency spectrum. Other possible components of a filter bank include downsamplers, upsamplers, and delay elements.

Figure 1: M channel filter bank

Figure 1 illustrates the structure used for the filter bank of M channels of discrete time, maximally divided. In the analysis stage, the input signal x[n] passes through a bank of M filters of Hi(z) Transfer Analysis. Each of these filters preserves a frequency band of uniform width equal to ⍰/M. The M signals are divided by M to maintain the sampling rate of the entire system. The resulting signals in the sub-bands can be encoded, processed or transmitted independently or jointly. The Process block (Fig. 1) groups all these activities together and is generally not considered a component of the filter bank. In the last stage of the FB, the sub-bands are combined by a group of over-samplers and M Fi(z) transfer synthesis filters, and thus obtain the reconstructed signal x'[n]. In ideal filters the aliasing effect is not presented, so a perfect reconstruction is achieved. In practice, and for similar behavior, it is necessary to make a careful choice of the parameters of Hi(z) and Fi(z).

The filters are designed by applying the Lapped Orthogonal Transform (LOT) which offers advantages compared to the Discrete Cosine transform since it allows each block to be transformed in an overlapping way allowing the signal to be reconstructed without discontinuity. The LOT transform generates a block made up of a 64x32 matrix.

As the filters designed are Finite Impulse Response (FIR), the resulting FB does not present aliasing, nor distortions of magnitude or phase, achieving perfect reconstruction. It is constituted with 32 linear phase filters and with a bandwidth of 5.6 Hz. Due to the subsampling process, the filters are operated once every 32 samples. The resulting sub-bands are computed at the cost of a filter and with high efficiency by the implementation of polyphase used.

Figure 2: (a) Original ECG, (b) Subsampled ECG, (c) Reconstructed ECG, (Abscissa: Number of samples, Ordered: Signal amplitude)

Figure 2 represents the signal form obtained with the Filter Bank. The original electrocardiographic signal is presented in Fig. 2(a), indicating on the horizontal axis the number of 6,144 samples processed, out of a total available in the signal extract of 30,000.

Fig. 2(b) shows the result of the downsampling process. This operator is a common processing block in the multi-tasking process. In generic form, the relationship between input and output is given by:

with M integer and equal to 32 for that matter. Since the YD(n) output consists of each M-th sample of the x(n) signal, the sampling rate is 1/M of that of x(n). Fig.2(a) shows the 192 samples processed by downsampling. The Z-transform of the sub-sampling operation is:

where:

The aliasing effect is avoided by limiting the input to □/M, before sub-sampling by the M factor. Figure 2(c) indicates the reconstructed ECG signal after processing by the filter bank. Note that as a result of the upsampling process, the number of original samples of the signal has been recovered. For the over-sampling operator, the relationship between the input and output signals is:

if n is an integer multiple of M otherwise with M integer (M=32). The over-sampling operation inserts M-1 zeros after each sample into the input. No information is lost during this operation because the input can be retrieved from YU(n) using an M-fold splitter.

The Z-transform of the over-sampling operation is given by:

- **Adaptive filters**
  The objective of the filter is to gain an estimate x´(n) of the sampled current signal x(n) from the values of the previous signal by means of an overlap, as follows:

  The coefficients are adjusted adaptively according to signal change statistics. A sampling rate of 500Hz and a filter with two leads have been shown to be sufficient for good prediction performance.

- **Combined filters**
  They are combinations of linear filters, after some kind of analog processing, the signal is digitized and processed through a low pass filter with a Notch filter and a passing filter, this scenario of digital filters is followed by a combined filter for a further improvement of the signal to noise ratio. The impulse response of the combined filter is taken from the first cycle of the measured input signal. To increase accuracy in time, the output of the combined filter will be interpolated 4 times the original sample rate. The final decision on the output signal is made by comparing the filtered signal with the set threshold.

- **Hilbert transform method**
  The Hilbert transformer is approximated by a band-limited FIR filter with 2N+1 leads. The Hilbert transform of the input signal is used to obtain the enveloping signal, which is limited in band. In order to reduce the curls of the envelope and avoid ambiguities in peak detection, the envelope is filtered by a low pass. In order to eliminate noise, the surround signal is smoothed by 4 leads moving the filter average.

- **Syntactic method**
  The signal to be analyzed by the syntactic method is assumed as a concatenation of primitive models represented linguistically (strings), the syntactic algorithm for model recognition essentially requires the definition of primitive models, a convenient linguistic representation (alphabet) and the formulation of the grammar of the models. In biomedical signal processing, the signal is divided into small segments of variable or fixed length, each segment is represented by a primitive and encoded using the predefined alphabet, due to its computational efficiency, more algorithms use line segments as primitives for the representation of the signal. Line segments can be extended to peaks, parabolic curves, and additional attributes.

In addition, methods such as:

- Processing of non-linear signals by means of neural networks.
- Neural networks as adaptive nonlinear predictors.
- Markov model. Mathematical morphology.
- Genetic algorithms.
- Transformation of length and energy.

CONCLUSIONS AND RECOMMENDATIONS

Once the topic covered in this article was placed through the use of workshops to be developed by the students, it was achieved that their understanding in the elaboration of the analysis of the signals under study resulted in various designs of signal processing algorithms to incorporate them into monitoring, protection and diagnosis instruments. The application of these methods is recommended under the development of workshops focused on other instruments such as Electromyographs, EEG, Electroencephalographs, EMG, Oculoretinographs, ORG, Blood Pressure Monitors, Holter, Pulse Oximeters, among others.

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