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Performance Evaluation of Various Window Techniques for Noise Cancellation from ECG Signal

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Abstract: *- ECG signal processing in an embedded platform is a challenge which has to deal with several issues. One of the commonest problems in ECG signal processing is baseline wander removal and noise suppression, which determine posterior signal process. In this report, two filtering techniques are presented and implemented to work on a Shimmer platform. Baseline wander removal based on cubic splines and morphological filtering are evaluated to check whether are suitable for real-time execution. The use of cubic splines is made to estimate the baseline wander in an ECG signal and then subtract it from the input dataset to remove the baseline wander. Morphological operators are useful for signal processing and noise suppression. These techniques have been implemented and tested by a wavelet-based delineation algorithm and results are provided for comparison purposes. The project goal is to develop an implementation for baseline wander removal and noise suppression to be executed on an embedded platform, meeting its specific hardware constraints, and leaving room for posterior signal processing. This would allow designing a Wireless Body Sensor Network to support non-ambulatory healthcare.*

Keywords: *ECG, signal processing, noise suppression, baseline correction, embedded platform, cubic spline, morphological filtering.*

1. INTRODUCTION

The function of the human body is based on signals of electrical, chemical or acoustic origin. Such signals provide information which may not be immediately perceived but which is hidden in the structure of the signal. This hidden information has to be decoded in some way before the signals can be given useful interpretations. The decoding of body signals has been found helpful in explaining and identifying several pathological conditions. This decoding process is sometimes easy to perform since only involves a limited manual effort such as visual inspection of the signal printed on a paper or in a computer screen. However, there are signals whose complexity is often considerable and, therefore, biomedical signal processing has become an indispensable tool for extracting clinically significant information hidden in the signal.

The process of biomedical signals is an interdisciplinary topic. It is needed some knowledge about the physiology of the human body to avoid the risk of designing an analysis method which may distort or even remove significant medical information. Of course, it is also valuable to have a good knowledge of other topics such as linear algebra, calculus, statistics and circuit design. Some decades ago, when computers first arrived in the area of medicine, automation was the main goal, but this has been modified over the years, since a physician must be ultimately responsible for the diagnostic decisions taken. Nowadays, the goal is develop computers systems which offer advanced aid to the physician in making decision.

2. WIRELESS BODY SENSOR NETWORKS

A Wireless Sensor Network -WSN- is a network composed of very small devices called nodes and, usually, a base station which stands for communication and nodes control. The nodes in a WSN are spread to measure a set of parameters and because of this, a wireless communication among nodes and between a node and a base station is needed.

There is a wide variety of issues, regarding science, government, health that calls for high fidelity and real-time observations of physical world. A network of smart wireless sensors could help to reveal what was previously unobserved in the location in which a phenomenon is taking place. Therefore, there is a challenge to design physically-coupled, robust, scalable and distributed systems based on embedded networked sensors. These nodes can help to monitor physical world and, by the use of its ad-hoc network, to coordinate and per-form high-level identification. The information gathered by those nodes can be processed to perform a real-time embedded analysis thanks to which several actions could be taken after deciding whatever it may be necessary.

3. THE SHIMMER PLATFORM

Shimmer [23] is a small wireless sensor platform designed to support wearable applications. Its size and technology stands for low power consumption so that it can be used as a test node for WBSN healthcare application.

It is based on the Texas Instrument MSP430F1611 processor, which works at a maximum frequency of 8MHz and has 10KB of RAM and 4KB of Flash memory. It is equipped with several peripherals such as digital I/O, analog to digital converters, 802.15.5 radio, Class 2 Bluetooth radio, a MicroSD slot and it is a proven solution in medical sensing applications. There is a ECG board daughter card to capture ECG data.

The MSP430F1611 is a 16-bit ultra low-power microcontroller based on RISC architecture. The CPU is integrated with 16 registers that provides reduced instruction execution time, since the register-to-register operation execution time is one cycle of the CPU clock long. The instruction set consists of 51 instructions with seven address modes. Each instruction can operate on word and byte data. 24 of these instructions are emulated: they do not have op-code themselves and are replaced automatically by the assembler with an equivalent core instruction.

The microcontroller does not have a floating point unit and all the floating point operations required are transformed into several integer compatible operations. It does not support hardware division but it has a hardware multiplier. All the division and multiplication operations by a multiple of 2 are converted into a shifting operation. The compiler provides translation for division operations into equivalent integer ones whereas the hardware multiplier is used to execute multiplications which cannot be translated.

4. STATE OF THE ART

The removal of the baseline wander in an ECG signal has been one of the first challenges in biomedical signal processing. The two major techniques employed for the removal of baseline wander are linear filtering and polynomial fitting.

The design of a linear, time-invariant, high pass filter involves the consideration of choosing the filter cut-off frequency and phase response characteristic. Obviously, the cut-off frequency should be chosen so that the clinical information in the ECG remains undistorted, so it is essential to find the lowest frequency component of the ECG spectrum. Since the heart beat is not regular it is needed to choose a lower cut-off frequency, approximately F_c = 0.5Hz. Linear phase filtering is needed to prevent phase distortion from altering characteristic waves in the cardiac cycle. Finite impulse response filters can have an exact linear phase response, whereas infinite impulse response -IIR- filters introduce signal distortion due to nonlinear phase response. To avoid this non-linear phase response in an IIR filter, the use of forward-backward filtering stands as a remedy since the overall result is filtering with a zero-phase transfer function.

Unfortunately, filtering based on that cut-off frequency cannot sufficiently remove baseline wander that may occur, for instance, during a stress test, so the use of a linear time-invariant filtering would limit the use of an implementation to an ambulatory resting context. For this purpose, calculate the heart rate as inversely proportional to the RR interval length is a simple but useful way. Then, it could be possible to relate a time-varying cut-off frequency $f_c(n)$ to the heart rate so that a low-pass filter could be integrated with the filter structure. Linear filtering based on filters with variable cut-off frequency was initially suggested for off-line processing of ECG signals [24] and then extended for use in on-line processing [25]. Other approaches to linear, time-variant filtering have also been described based on adaptive, LMS techniques [26].

An alternative to baseline wander removal with linear filtering is to fit a polynomial to representative samples of the ECG, with one knot being defined for each beat. The polynomial estimating the baseline is fitted by requiring it to pass through each of the knot smoothly. This technique requires that the QRS complexes first be detected and it needs the PQ intervals to be accurately detected. This baseline wander removal technique is implemented and evaluated in this project.

Muscle noise -electromyography noise- is a major problem in many ECG applications. Muscle noise is not removed by narrowband filtering but represents a much more difficult problem since the spectral content of muscle activity considerably overlaps that of the PQRST complex. Successful noise reduction by ensemble averaging is, however restricted to one particular QRS morphology at a time and requires several beats to work properly. One approach to muscle noise filtering is to use a filter with a variable frequency response, such as a Gaussian impulse response. The resulting performance on ECG signal of these techniques can be found in [27]. An application of this variable frequency response filtering to the baseline wander removal challenge can be found on [28]. However, time-varying properties may introduce artificial waves: a filter that provides considerable smoothing of the low-frequency ECG segments outside the QRS complex is likely to result in undesirable effects during the transitional periods. This distortion renders the filtered signal unsuitable for diagnostic interpretation of the ECG. There is a host of additional techniques to muscle noise reduction, but no single method has gained wide acceptance for use in clinical routing. As a result, the muscle noise problem remains largely unsolved.

5. DESCRIPTION

The following process of baseline wander removal is based on the paper by C. R. Meyer and H. N. Keiser [4]. There have been several approaches, as explained above, to the baseline wander removal problem. The technique here presented uses a polynomial to try to adapt to the baseline wander. In each beat, a representative sample is defined and called “knot”. These knots in the input signal are chosen from the silent isoelectric line which, in most heart rhythms, is represented by the PQ interval.

This technique comes from the work of some investigators who tried to adapt a straight-line to the segments connecting the pre-P-wave period and the post-T-wave period of each beat as successive baseline estimates. While this solution preserves low-frequency heart activity and leads to a small computational cost, such a first-order estimator can only accurately track baselines of very low frequencies [12]. Furthermore, the resulting baseline estimate does not adapt properly to the variations and, what is worse, its derivatives at the knots are discontinuous.

Increasing the order of the polynomial and selecting one knot per beat through which the baseline estimation must pass is the method used to remove higher-frequency baseline noise and preserve low-frequency heart information, which is useful for other processes to apply after the baseline wander removal. By using higher-order polynomials, the likelihood of producing an accurate baseline estimate increases, although it is obviously linked to an increased computational complexity.

Instead of letting the order increase as the number of knots does, third order polynomial fitting to successive triplets of knots represents a popular approach [4 and 13] and leads to good results in terms of baseline removal. This technique requires the QRS complexes to be detected and the corresponding PQ intervals to be accurately determined. It is chosen one averaged point in each PQ segment of the ECG as sample of the baseline. This segment is used because of the ease and accuracy in locating it.

At each PQ segment there is a knot through which the baseline noise estimator must pass. By fitting a third-order polynomial through these knots in the ECG signal we get the estimation for the baseline. These knots could be also defined by the end of the P wave. The polynomial is fitted in such a way that, one subtracted to the original signal, these knots have a value of 0.

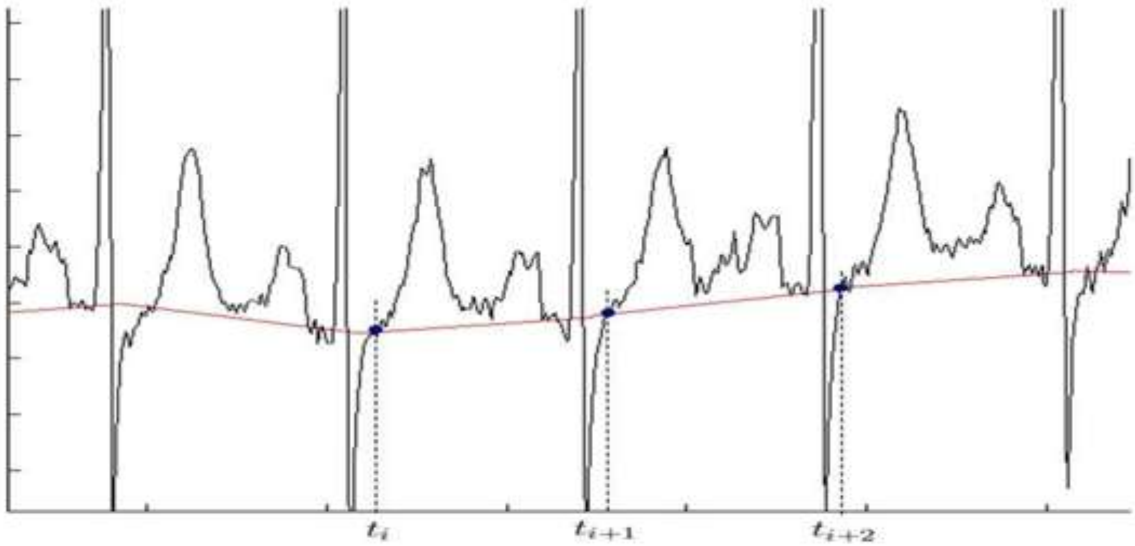

Figure: - ECG signal with three knots and the cubic spline baseline wander estimation y(t)

This technique intuitively approaches the benefits of using Lagrange's method to define a polynomial passing through all of the PQ-segment knots of the total ECG record without the penalties in complexity associated to high-order polynomials. If we used Lagrange's method over a 20 sec record of ECG at 60bpm, the result would be nearly a 20th-order polynomial to be evaluated at each sample point in the record.

The use of this technique in an embedded platform has to consider the fact that we need to define accurately the PQ interval in each beat. Fortunately, the paper suggests a PQ-segment locator, although we have had to redefine its working process. Furthermore, computing the polynomial in the interval of the input signal which is between three following beats leads to a memory consumption which has to be taken into consideration, as shown below. Finally, the function used to fit the polynomial requires some operations that are not easy to perform in an embedded platform as the MSP430.

The first step is to locate the knots of the successive beats in the input signal. These knots are denoted for the signal x(t) as

$$x(t_i),\ i = 0, 1, 2, \dots ,$$

The baseline estimate y(t) is computed for the interval $[t_i, t_{i+1}]$ by incorporating the three knots $x(t_i)$, $x(t_{i+1})$, $x(t_{i+2})$ into the Taylor series expanded around t_i.

$$y_\infty(t) = \sum_{l=0}^{\infty} \frac{(t - t_i)^l}{l!} y_\infty^{(l)}(t_i)$$

For a third-order polynomial description, this series is truncated to

$$y(t) = y(t_i) + (t - t_i)y'(t_i) + \frac{(t - t_i)^2}{2} y''(t_i) + \frac{(t - t_i)^3}{6} y'''(t_i)$$

And the series expansion for the first derivative $y'(t)$ is

$$y'(t) = y'(t_i) + (t - t_i)y''(t_i) + \frac{(t - t_i)^2}{2} y'''(t_i)$$

At t = 0 we assume, to get this technique working, that

$$y(0) = x(0)$$

We must approximate the first derivative $y'(t_i)$ at t_i by the slope between

$x(t_{i+1})$ and $x(t_i)$

$$y'(t_i) = \frac{x(t_{i+1}) - x(t_i)}{t_{i+1} - t_i}$$

As shown in [14], classical splines of order three and higher, in which only the highest derivative is discontinuous, suffer stability problems during computation so we define both $y(t)$ and $y'(t)$ at each knot to arrive at a stable solution.

At the next beat, and to keep the cubic spline adapted to pass through all the knots considered, we must approximate, once more,

$$y'(t_{i+1}) = \frac{x(t_{i+2}) - x(t_i)}{t_{i+2} - t_i}$$

To find the remaining two variables $y''(t_i)$ and $y'''(t_i)$ in $y(t)$ the Taylor series for $y(t)$ and $y'(t)$ is studied for $t = t_{i+1}$

$$y(t_{i+1}) = y(t_i) + y'(t_i)(t_{i+1} - t_i) + y''(t_i)\frac{(t_{i+1} - t_i)^2}{2} + y'''(t_i)\frac{(t_{i+1} - t_i)^3}{6}$$

and

$$y'(t_{i+1}) = y'(t_i) + y''(t_i)(t_{i+1} - t_i) + y'''(t_i)\frac{(t_{i+1} - t_i)^2}{2}$$

To get the cubic spline to pass through this knot

$$y(t_{i+1}) = x(t_{i+1})$$

Inserting these values of $y(t_{i+1})$ and $y'(t_{i+1})$ into the previous equations we get

$$y''(t_i) = \frac{6(y(t_{i+1}) - y(t_i))}{(t_{i+1} - t_i)^2} - \frac{2\left(2y'(t_i) + \frac{y(t_{i+2}) - y(t_i)}{t_{i+2} - t_i}\right)}{t_{i+1} - t_i}$$

$$y'''(t_i) = -\frac{12(y(t_{i+1}) - y(t_i))}{\quad} + \frac{6\left(y'(t_i) + \frac{y(t_{i+2}) - y(t_i)}{t_{i+1} - t_i}\right)}{\quad}$$

where, as we know, $(t_{i+1} - t_i)^3$ $(t_{i+1} - t_i)^2$

$$y(t_{i+2}) = x(t_{i+2})$$

We have then the baseline estimate y(t) completely specified to be computed in the interval $[t_i, t_{i+1}]$. To get the signal without baseline wander we have to subtract from the ECG signal samples in that interval the baseline estimate y(t). Then, this procedure has to be repeated for the next interval $[t_{i+1}, t_{i+2}]$ using the knots x_{i+1}, x_{i+2} and so on.

The performance of the cubic spline technique is critically dependent on the accuracy of the knot determination. The PQ interval is relatively easy to delimit in ECGs recorded during resting conditions but it may be difficult to find in recordings with muscle noise or when certain types of arrhythmias are present, such as ventricular tachycardia, which distorts severely the ECG signal and makes the location process almost impossible. When these circumstances take place, the PQ interval is not well-defined and, therefore, this technique is inapplicable.

The first step in locating the PQ-interval knot is to detect the Q-wave's maximum downslope. The downslope of the ECG signal at any sample with time index t is computed using an average negative slope estimate where

$$\text{downslope}(t) = x(t-3) + x(t-1) - x(t+1) - x(t+3)$$

Since we are using a 250Hz sampling frequency, the time interval between two adjacent samples is 2msec. It is defined to detect the maximum downslope in the working sample when the computed downslope value exceeds 60% of the previous maximum.

Once the PQ-knot is located following the previous procedure, the ordinal value for the knot is calculated as the average ordinal value of the four data points which are nearest to the sample in which the knot has been detected. Using these four points to estimate the ordinal value of the knot eliminates the
Effects of the 60Hz noise, according to the data sampling frequency of 250Hz: an average over four points acquired at 250Hz spans 16msec or nearly one cycle of 60Hz noise. As shown in [4], from digital filtering theory, we know that averages consisting of symmetrically space points spreading exactly over one cycle of a sinusoidal signal are not biased by that signal component.

At this point, we are able to implement the technique proposed for baseline wander removal: we must get the locator working to calculate, for each data sample, the down slope. If the computed down slope exceeds 60% of the previous maximum, we know that the knot is 17 data samples (66msec at 250Hz) before the point which triggers the down slope. Then, by averaging the four points next to and including this sample, we get the ordinal value of the knot, which is going to be considered as $x(t_i)$. As shown before, we need three consecutive beats which its correspondent knots to start calculating the cubic spline, so we need to store in memory the data samples from the knot at t_i to the last sample of the third beat and, when it is completed, process the first beat.

This takes a lot of memory to operate so, in the next section, it is explained the implementation proposed and some optimizations to the knot locator**.**

6. CONCLUSION

To measure the results of these filtering techniques, we are going to use a wavelet based ECG delineation algorithm by Nicholas Boichat [10]. This de-lineation algorithm is based on the wavelet transform which was first presented in [18] and developed in [19]. The delineation process takes advantage of the fact that the ECG is roughly a periodic signal, and each beat is composed of a QRS complex, preceded by a P wave, and followed by a T wave. Each of these waves has different frequency content -the QRS complex is made by relatively high frequencies, while the P and T waves are composed of low frequencies.

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