

# ADAPTIVE MOTION ARTIFACT FILTER FOR PHOTOPLETHYSMOGRAM EXTRACTION

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**Abstract:** Adaptive filters have been used to enable the robust measurement of photoplethysmogram (PPG) under conditions of the motion artifact which causes a high noise to the signal. In this adaptive filter a noise reference and a signal reference are used. The least mean square (LMS) method was applied to extract the actual signal from the noisy one. For the first approximation to generate the reference signal, a low pass filter is used. Based on the resulting signal, an appropriate reference signal is generated. This reference signal is in turn subtracted from the detected signal to generate a noise signal. The generated noise signal is modified to synthesize the noise reference signal. The synthesized reference noise is adjusted by the adaptive algorithm to the real one contained in the measurement, and then subtracted from the detected noisy signal. The filtered signals can be used to determine various physiological parameters such as the fractional oxygen saturation or the other blood components. Calculating the oxygen saturation using the filtered PPGs subjected to artifacts looks promising when compared to the calculated values using PPGs without motion artifacts, for the same case.

## 1 INTRODUCTION

The photoplethysmogram (PPG) plays a central role for noninvasive monitoring and early diagnosis. Not only will PPG and the principle of spectroscopy be used to calculate oxygen saturation and biochemical concentrations in blood like hemoglobin and glucose, but also in combination with other measured parameters it will be used to calculate more parameters and hence enables a valuable diagnosis (Mendelson, 1992), (Ali-Munive, 2002).

Pulse oximetry is a valuable and widely employed non-invasive method to monitor oxygen saturation. But motion artifacts, especially for monitoring the fractional oxygen saturation, entail great limitations and often become an insurmountable obstacle in the utilization of this technology, since they appear in the same frequencies as the desired signal and their amplitude order is quite large compared to the amplitude levels of pulse signals. Due to this frequencies overlap, indiscriminate filtering cannot be tolerated, for reasons of signal clarity preservation (Abdallah, 2003), (Vora, 2004), (Masimo Corporation).

In order to develop a multisensor for diagnosing cardiovascular diseases and computing the fractional

oxygen saturation, an adaptive filter, that allows the detection of the PPG by one or more sensors under conditions of motion artifacts, has been explored. By this way, it will be possible to establish the fractional oxygen saturation values even under motion circumstances. The main advantage of the algorithm implementing the adaptive filter is that it needs just one PPG.

To develop a full-featured system successfully without any other help, else one PPG signal, an implementation based on a noise cancellation configuration is carried out and the noise reference necessary for its proper operation is synthesized from the PPG signal itself. Amongst all the possible adaptive algorithms that can be used, due to its low computational cost, the Least Mean Square algorithm has been selected, which improves the quality of the PPGs by cancelling the effects of motion artifacts.

Many experiments are performed to test the capabilities of the proposed system. The results indicate that the effects of motion artifacts are to a large extent cancelled and the recovered PPG signal's quality is good enough for measuring the fractional oxygen saturation of the haemoglobin in blood. Further blood contents like glucose and physiological parameters can be extracted in a way

that could allow monitoring them under artifacts.

## 2 METHOD

When a conventional adaptive filter system has to be used, the first requirement consists of having two signals:

- The input signal coming from the sensor.
- A reference signal that has to be an ideal version of the input signal, as the adaptive algorithm works to make the input signal as similar as possible to the reference signal.

The first decision was to reject the use of a conventional adaptive filter implementation, because a priori there is no reference pulse signal for a given person at every moment. So, we considered an adaptive noise cancellation system as possible solution. But, when we use an adaptive noise cancellation system, two input signals are needed again; now they are:

- The input signal or, expressed in other words, the measurement coming from the sensor. That is to say, the same requirement as the one presented above.
- A noise reference signal that must be similar to the real noise that our measurements contain, but not necessarily equal to it, as in this case, the filter tries to eliminate this real noise while leaving the desired signal (pulse signal) unchanged. That is a great advantage compared to having to generate a perfect pulse signal, as unlike synthesizing a pulse reference, synthesizing a noise reference similar to the real noise coming from the sensor is actually feasible.

We do not have that noise reference signal at our disposal, and this fact leads us to synthesize this second input by designing a synthesizer.

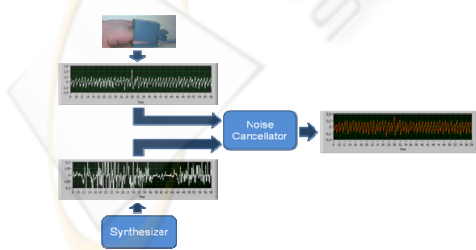


Figure 1: Block diagram of the Main Program.

A broad outline of the implementation of the algorithm that has been devised is given in Figure 1, where the interaction between the two principal cornerstones of the design, the Adaptive Noise

Cancellation System and the Noise Reference Synthesizer, can be noticed. Once we have correctly generated a Noise Reference Signal by means of the Synthesizer, it will be adjusted as much as possible to the real noise contained in the corresponding measurement by the adaptive filter. In our case, this filter is composed of a noise cancellation configuration which uses a Least Mean Square algorithm as adaptive algorithm. What we get as output from the system is a denoised pulse signal.

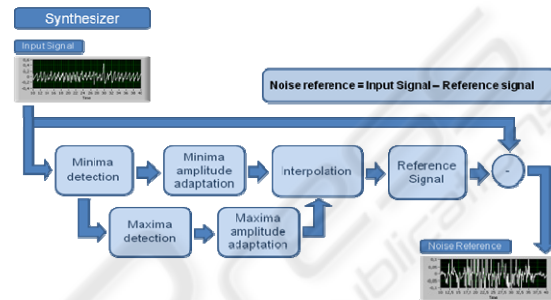


Figure 2: Block diagram of the Synthesizer.

The Synthesizer generates a Noise Reference, which is necessary for the Adaptive Noise Cancellation System, by means of generating an ideal pulse signal, called Pulse Reference Signal. Figure 2 presents the basic block diagram of this Synthesizer.

Given that the Reference Signal has to follow the Input Signal, it has to be created according to the current Input Signal at each moment. For that reason, it is, first of all, required to know the number of periods that the corresponding Input signal has. Therefore, in the Minima Detection block we search and find all the pulse minima locations in the Input Signal, since there are as many periods as there are minima-1. In order to generate a more reliable Reference Signal, the amplitude values of these minima are also calculated along with the locations and amplitude values of the maxima appearing in the Input Signal, using the Maxima Detection block. Each minimum and maximum's amplitude are adjusted to the corresponding Input Signal period. Using the Interpolation block, the Reference Signal is generated with as many periods as the current Input Signal and with the same amplitude. Once this pulse reference signal, Reference Signal, is generated, we are able to obtain a noise model by the following equation:

$$\text{Noise Reference} = \text{Input Signal} - \text{Reference Signal} \quad (1)$$

As previously mentioned, an adaptive noise cancellation system has two inputs, as shown in Figure 3. One is the Input Signal, i.e. the signal

corrupted by noise, coming from the sensor, and the other one is the Noise Reference, coming from the Synthesizer output. Given that the Least Mean Square algorithm provides adaptive filtering, the Noise Reference is adjusted to the real noise measured by the sensor and, as a result, the output, Filtered Signal, naturally is the denoised signal.

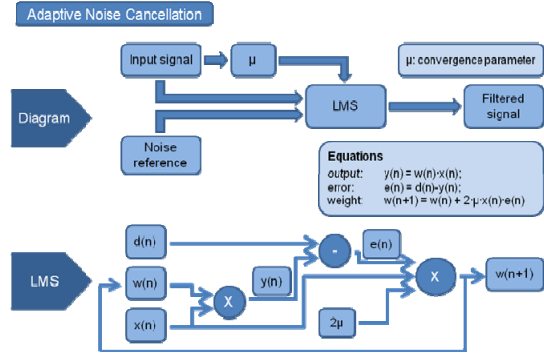


Figure 3: Block diagram of the Adaptive Noise Cancellation (ANC).

### 3 RESULTS

To make possible SpO<sub>2</sub> measurements, we need to compare two PPGs at the same time with two different wavelengths. For that reason, we required a multi-wavelength featured sensor such as the PHM used at the institute's laboratory, which has eight different LEDs.

In order to test our system capabilities, it was essential to obtain somehow measurements with the employed PHM sensor that simulates those taken in real situations in which PPGs presents drawbacks that make computing medical parameters by means of photoplethysmography unfeasible.

With the purpose of simulating these kinds of conditions at our laboratory, the sensor was subjected to movement, thereby emulating typical motion artifacts that are usually presented in the pulse signal when it is measured under extreme conditions such as within a moving ambulance.

The measurements were carried out alternatively between intervals of time without movement and intervals with movement of the finger, hand and even arm varying in speed and intensity. Each measurement from this PHM sensor contains as many signals as LEDs on. Since we need two of them, first we have to separate the signals. Once these single signals are presented separately, we select two of them that have been measured with the proper wavelengths value like 970 nm and 660 nm.

Then they are already adapted for being filtered by our system. Finally, the filtered signals obtained after the program execution can already be used to compute ratios regarding the SpO<sub>2</sub>, such as the so-called  $\Omega$  ratio:

$$\Omega = \frac{\ln \frac{I(\lambda_1, t_1)}{I(\lambda_1, t_2)}}{\ln \frac{I(\lambda_2, t_1)}{I(\lambda_2, t_2)}} \quad (2)$$

Where:

$I(\lambda_1, t_1)$ ,  $I(\lambda_1, t_2)$ ,  $I(\lambda_2, t_1)$  and  $I(\lambda_2, t_2)$  are the light intensities measured at the instants  $t_1$  and  $t_2$ , with the wavelengths  $\lambda_1$  and  $\lambda_2$ , respectively.

As results, examples of each step of the process described here are presented. First of all, examples of the appearance of PHM measurements (and therefore, multi-wavelength measurements) are shown, both the whole measurement and a zoom of it. Next, the output given by the recovery of each single signal coming from only one LED is also presented. To demonstrate the ability of the proposed system to make possible a precise enough computation of the SpO<sub>2</sub>, we have calculated the value of the above-named  $\Omega$  ratio for several measurements. In order to make sure that the adaptive filter works well enough to get accurate SpO<sub>2</sub> readings, the main goals are: first, to prove that the ratios obtained are included in an acceptable range (bearing in mind that the values of this ratio allow us to estimate the calibration that has to be applied later to the exact calculation of the SpO<sub>2</sub>). Next, it must be proved that the values for the ratio when the signal is affected by motion artifacts keep quite unchanging compared to those stretches of the same signal where there is no noise.

Figure 4, shows the PHM measurements. There are seven emitting diodes; each signal coming from each LED presents a different mean amplitude level and a reference level. After the recovery of each single signal, and once the reference level has been subtracted, the outcome of the Figure 5 is given, which is the result of recovering each single signal contained in the previous measurement.

From the group of four graphs on the top of the Figure 6, the two on the left are parts (delimited by  $t_0$  and  $t_1$ ) without noise of two signals from the same PHM measurement, corresponding to the signal coming from the LED configured with infrared wavelength and the LED configured with red wavelength.

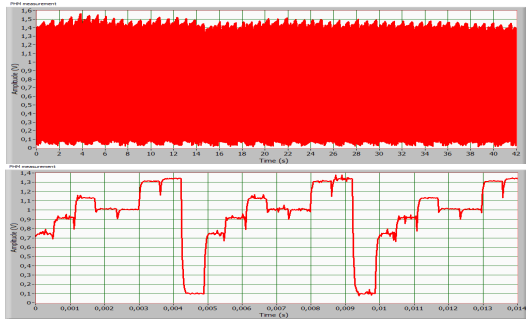


Figure 4: PHM measurement and detail of the different signals appearing in the PHM measurement.

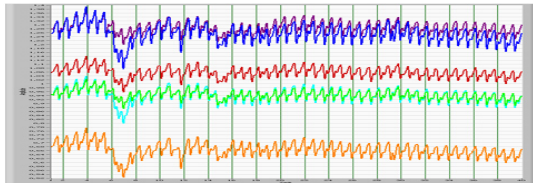


Figure 5: Signals recovered from a PHM measurement.

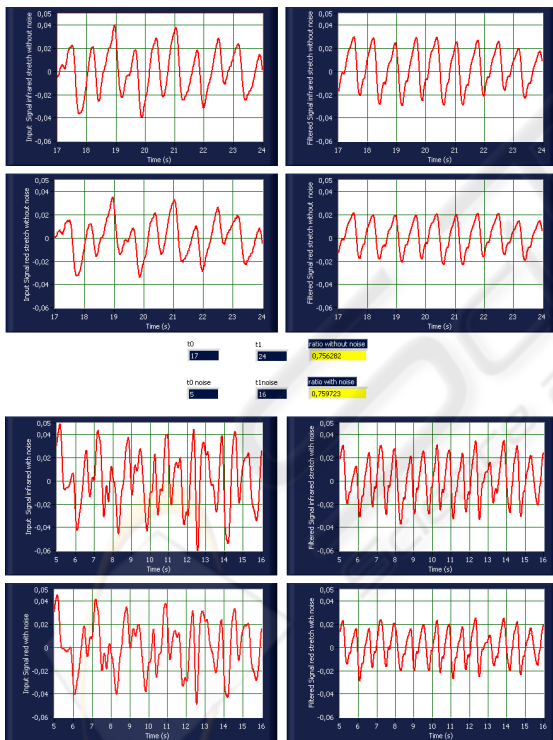


Figure 6: LabVIEW printing for filtering a PHM measurement and computing  $\Omega$ .

The two plots on the right are the result of filtering these two signals. Analogously, the group of four graphs on the bottom represents two parts (delimited by  $t_0$  noise and  $t_1$  noise) with noise of the same two signals from the same PHM measurement. In the

middle, the two values for the ratio  $\Omega$ , one corresponding to the noisy stretch of the signals and the other one corresponding to the clean stretch are presented.

## 4 CONCLUSIONS

Both, for long-term and short-term monitoring (for example, in case of an emergency) of biosignals, the use of an adaptive filter becomes essential. The developed algorithm implementing the adaptive filter is applicable to the PPG signal, which is needed for the computation of several vital parameters (such as SpO<sub>2</sub>, HR and blood pressure fluctuations) and also for diagnosing. In fact, the results indicate that the signal recovered from this implementation has enough quality for measuring the fractional oxygen saturation of the haemoglobin in blood.

Furthermore, after a few modifications, this algorithm can be used for electrocardiogram (ECG) and it is also possible to carry out more adjustments to other parameters such as electroencephalogram (EEG), electrooculogram (EOG) and fetal ECG (FECG).

## REFERENCES

Abdallah, O., 2004, Optical Non-invasive Calculation of Hemoglobin Components concentrations and Fractional oxygen Saturation Using a Ring Scatterin Pulse Oximeter, Proc. of the SPIE-Photonics West (BIOS), Volume 5325, pp. 51-61, San Jose, USA.

Ali-Munive A., Rodriguez P., Gomez S., Arce A. M. and Rodriguez E., 2002, Correlación entre Pulsioximetría y Saturación Arterial de Oxígeno en Pacientes en Cuidado Intensivo, Bogotá.

Masimo Corporation, <http://www.masimo.com>

Mendelson Y., 1992, Pulse Oximetry: Theory and Applications for Noninvasive Monitoring, Clinical Chemistry, Vol. 38, No. 9, pp. 1601-1607, Worcester.

Vora Vadana A. and Ahmedzai, S. H., 2004, Pulse Oximetry in supportive and palliative care, Vol. 12, No. 11, pp. 758-761, Sheffield, UK.