

Research on the Filter Design for Oximetry Monitors

Wenhan Yan^{1,a,*}

¹Academy of Integrated Circuits, Dalian University of Technology, Dalian, 116000, China

a. 2531207835@qq.com

*corresponding author

Abstract: Blood oxygen saturation is an important parameter of the respiratory system, and its monitoring is crucial during clinical ambulance operations, but the accuracy and integration of current oximeters need to be improved. In order to cope with the inevitable noise interference in the oximetry detection, the current oximetry monitors often use Kalman filtering FIR filtering, and other algorithms to optimize the detection signal. However, these filters have certain limitations in dealing with ambient light changes and different scenarios. For this reason, this paper proposes an adaptive filtering algorithm. In this algorithm, in a specific signal - processing situation, the noise signal is superimposed on the original signal after the unknown system undergoes a linear change, thus forming the desired signal. The noise signal enters the adaptive filter as an input, and the adaptive algorithm inside the filter makes the noise signal as close as possible to the state of the unknown system in the natural environment and generates an output signal. The noise in the desired signal is canceled out by the negative feedback mechanism and an error signal is obtained. The error signal is fed back to the adaptive filter, which updates its weights and then continues with the next filtering operation, and so on to achieve continuous optimization of the signal.

Keywords: blood oxygen saturation, adaptive algorithm, noise treatment, Kalman filter, FIR filter

1. Introduction

Blood oxygen saturation (SpO₂) refers to the percentage of the volume of oxygen - combined hemoglobin (HbO₂) in the blood relative to the volume of all combinable hemoglobin (Hb). In other words, it represents the concentration of oxygen in the blood. SpO₂ is an important parameter in the respiratory system. Many respiratory disorders cause a decrease in blood oxygen concentration, and circulatory failure blood oxygen saturation decreases accordingly. Therefore, the monitoring of blood oxygen saturation becomes extremely important, especially in clinical care, and is essential in critically ill patients [1][2].

In recent years, the development of oximetry monitors has been remarkable. Technically, the development of oximetry monitors is committed to improving the accuracy and stability of the instrument and effectively reducing the influence of low perfusion, motion artifacts and other disturbing factors on the measurement [3]. In terms of device form, oximeters present a significant trend of miniaturization and portability, which facilitates the monitoring of relevant parameters over a long period of time and on a continuous basis [4]. In terms of function, oximeter is no longer limited to a single oxygen detection function, but integrates a variety of parameter measurements and

analyzes the measurement data in depth by combining artificial intelligence and big data to realize health management and early screening of diseases [5].

At present, the accuracy and integration of oximetry still have room for improvement. Oximeters need to be adapted to different skin tones, ambient light conditions, and motion states. For example, according to the simulation of Deng Zhenjin's team, which concluded that the finger-ring oximeter superimposes a weak pulse or a weak perfusion of 60Hz or 1-10 kHz of noise on the blood pressure waveform, and the SpO₂ and pulse rate display readings then exceed the manufacturer's claimed range of accuracy [6]. Therefore, in this thesis, we wish to combine the PPG technique (photoelectric volumetric pulse wave tracing) and adaptive noise cancellation to minimize the effect of factors such as ambient light on oximetry measurements.

2. Literature Review

2.1. Principle of Pulse Oximetry Monitor

Most pulse oximetry monitoring devices commonly contain an emitter, which is usually a light emitting diode (LED), and a light detector in the form of a photodiode. At least two wavelengths of light pass through human tissue (usually fingers, earlobes). The meter either transmits the light (transmitted oximetry) or reflects the light (reflected oximetry). The change in light intensity is primarily attributed to arterial pulsation. Due to the different absorption and reflection properties of hemoglobin for specific light in different states of the blood, this difference is then used to calculate blood oxygen saturation following the Lambert - Beer law.[7]

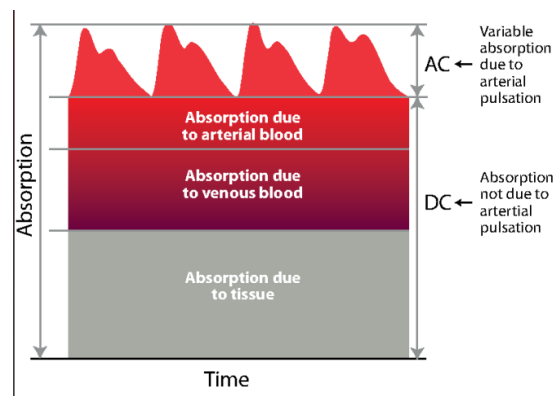


Figure 1: Electrical signals converted by the light detector



Figure 2: Pulsatile (AC) component of the PPG signal and the corresponding electrocardiogram (ECG)

The signal depicted in Figure 1 represents the electrical signal that has been converted by a photodetector [7]. The pulsatile component of the PPG waveform, frequently referred to as the 'AC' component, has a fundamental frequency typically around 1 Hz, which is contingent upon the heart rate as shown in figure 2 [8]. This AC component is superimposed upon a substantially larger quasi

- DC component associated with tissue characteristics and mean blood volume. The DC component, in turn, varies slowly as a consequence of respiration, as detailed in references [8] and [9].

2.2. Algorithms of commonly used oximetry monitors and their limitations

Filtering algorithms commonly used in oximetry monitors today are Kalman filtering algorithm, FIR filtering algorithm and so on.

Kalman filtering is founded on the minimum mean - square error as the optimal criterion for estimation. It is more suitable for recursive - estimation calculations when dealing with a relatively small amount of data. The linear system state equation is utilized to optimize the system state through the system input and output observations. These observations include the effect of noise and disturbances on the oximetry measurements, so that the filtering effect can be achieved [10][11].

FIR filtering is mainly a window function method, frequency domain sampling method, and other ripple best approximation methods, and so on. The unit impulse response $h(n)$ of the FIR digital filter is of finite length, and its expression for the low-pass filter frequency response function $H_d(e^{j\omega})$ is as follows:

$$H_d(e^{j\omega}) = \begin{cases} e^{-j\omega a}, & |\omega| < \omega_c \\ 0, & \omega_c < |\omega| < \pi \end{cases} \quad (1)$$

The idea of FIR digital filter design is to find an actual response frequency function $H(e^{j\omega})$ that maximally approximates the frequency response function $H_d(e^{j\omega})$ of the proposed design, which is designed by using a window function from the time domain point of view, and by using the frequency domain sampling method from the frequency domain point of view [12].

The limitations of these two filtering algorithms in handling ambient - light changes and other scenarios are mainly manifested in the restricted applicability of their filtering models. For example, Kalman filtering algorithm has a better fitting effect for signals obeying Gaussian white noise distribution, but when the monitoring environment, such as the frequent flashing of flash lamps and other situations, the noise will show more obvious non-Gaussian white noise characteristics, which affects the filtering effect [13]. The FIR filter also lacks sufficient adaptive ability, and its filtering characteristics are often determined by its coefficients, which can easily affect the filtering effect of the FIR filter when the ambient light intensity, frequency and other changes occur.

3. Methodology

To address the limitations of Kalman filtering and FIR filtering, we would like to use adaptive filtering algorithms in oximetry detection, a filtering algorithm that solves for the weighting coefficients when the a priori statistical conditions are unknown and thus performs noise filtering.

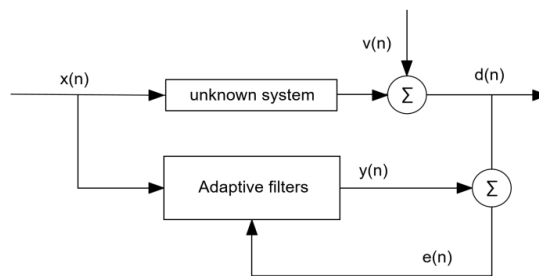


Figure 3: Block diagram of the adaptive system

As in Figure 3, in a particular signal processing situation, the noise signal $x(n)$ undergoes a linear change as it passes through a certain unknown system [14]. Subsequently, this changed noise signal is superimposed with the original signal $v(n)$, which in turn forms the desired signal $d(n)$. Throughout the processing, the noise signal $x(n)$ is provided as input to the adaptive filter. Inside the adaptive filter, the noise signal is processed with the help of an adaptive algorithm so that the noise signal is as close as possible to the state that it would be in a natural environment after passing through an unknown system. After processing the noise signal $x(n)$, the adaptive filter produces an output signal $y(n)$. This output signal $y(n)$ will perform pairwise cancellation of the noise signal contained in the desired signal $d(n)$ through a negative feedback mechanism. After this pair cancellation operation, the error signal $e(n)$ is obtained. The obtained error signal $e(n)$ is fed back to the adaptive filter. Based on the received error signal $e(n)$, the adaptive filter updates its own weights accordingly. After the completion of the weights update, the adaptive filter will continue to carry out the next filtering operation, and so on, to achieve the continuous optimization of the signal processing [14].

Based on this logic, we design an adaptive filter. The core of adaptive filtering is to let the filter automatically adjust the parameters according to the signal characteristics to realize efficient filtering. In the initialization session, we determine the filter order, step size and initial coefficients. The filter order determines the number of references to the past signal samples, which affects the filter's ability to capture the signal characteristics; the higher the order, the better the long-term characteristics are grasped, but the larger the computational volume; the step size controls the coefficients updating amplitude, which is too small for slow convergence and too large for instability. Into the sample-by-sample processing stage, for each input sample, according to the filter order to select the current and the past several moments of data to form the input vector, and then use the current coefficients and the input vector for the dot-multiplication summing operation, resulting in a predicted output. This output is an estimate of the true signal value. Next, the error between the predicted output and the desired output is calculated. This error visualizes how much the prediction deviates from the true value and is the key basis for adjusting the coefficients. Based on the error, combined with the step size and input vector to update coefficients, the specific algorithm is as follows:

$$\begin{aligned} &\text{new coefficient} = \\ &\text{old coefficient} + \text{step size} \times \text{inaccuracy} \times \text{transpose of the input vector} \end{aligned} \quad (2)$$

This calculation causes the coefficients to change in the direction of error reduction. The above process is repeated continuously, and the coefficients are gradually adapted to the signal characteristics as more samples are processed. Eventually, the coefficients tend to be stable, effectively suppressing the noise, maximizing the retention of the useful information of the original signal, and realizing adaptive filtering.

4. Results

In order to verify the effect of the adaptive filter, we simulated the oximetry detection signal interfered by ambient light in MATLAB, and in order to better and more comprehensively approximate the interference of complex light sources in real environments, we superimposed noise signals including Gaussian white noise, scattering grain noise, and scintillation noise on the ideal oximetry detection signal to simulate the oximetry signal detected in practice, and then filtered this signal by adaptive filtering, Kalman filtering, FIR filtering three filtering methods were used to filter the signal, and the filtering effect under complex ambient light was examined by comparing the final mean square error (MSE) size of the three filtering models. The blood oxygen saturation signal simulated in the experiment consists of numerous signals, and its specific composition is as follows:

$$\text{Original blood oxygen saturation signal: } s(t) = \sin(0.1t) \quad (3)$$

This formula uses the sine function to simulate the original blood oxygen signal. The angular frequency is 0.1, which means the signal will fluctuate with a certain period, simulating the periodic change of human blood oxygen over time.

$$\text{Gaussian white noise: } n_{\text{gaussian}}(t) = 0.3 \times N(0,1) \quad (4)$$

$N(0,1)$ represents the standard Gaussian distribution with a mean of 0 and a variance of 1. The coefficient 0.3 is used to adjust the amplitude of the noise. This noise simulates the random interference with Gaussian distribution characteristics commonly existing in the environment. Its power spectral density is uniform at all frequencies, so it is called white noise.

$$\text{Scattering grain noise: } n_{\text{Scattering}}(t) = 0.2 \times \text{Poisson}(0.5) \quad (5)$$

$\text{Poisson}(0.5)$ represents the Poisson distribution with a parameter of 0.5. The Poisson distribution is often used to describe the number of random events occurring in a certain time or space. The coefficient 0.2 is used to adjust the amplitude of the noise. Shot noise is usually related to the discreteness of photons in optoelectronic devices, simulating the random fluctuations of photons reaching the detector.

$$\begin{aligned} \text{Scintillation noise: } f &= \frac{1:N}{N} \\ \text{psd} &= \frac{1}{f} \\ \text{phase} &= 2\pi \times \text{rand}(1, N) \\ n_{\text{Scintillation}}(t) &= 0.4 \times \text{real}\left(\text{ifft}\left(\sqrt{\text{psd}} \times \exp(j \times \text{phase})\right)\right) \end{aligned} \quad (6)$$

In the first step, the frequency vector f and the power spectral density psd are defined. psd is inversely proportional to the frequency f , which reflects the characteristics of $1/f$ noise, that is, the noise power is larger in the low-frequency band and smaller in the high-frequency band. In the second step, a random phase vector phase is generated to simulate the randomness of the noise. In the third step, the power spectrum and phase information in the frequency domain are converted to the time domain through the inverse Fourier transform (ifft). The coefficient 0.4 is used to adjust the amplitude of the noise.

As shown in Figure 4 and Table 1, the five graphs represent the original blood - oxygen signal, the signal after noise interference, and the signals after adaptive filtering, Kalman filtering, and FIR filtering respectively. The MSE of the waveform after adaptive filtering is the smallest, 0.014189. It can be seen that when the oximetry monitoring device is under more complex ambient - light interference, the adaptive filter designed in this paper can reduce the interference of ambient light on the oximetry detection more effectively than the commonly used Kalman filtering algorithm and FIR filtering algorithm.

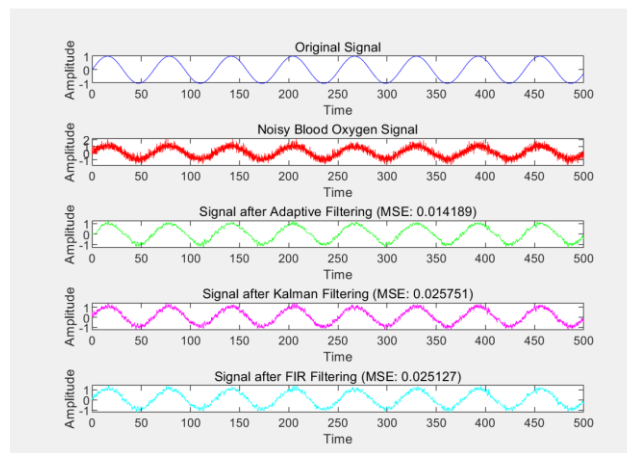


Figure 4: Verification of adaptive filtering effect

Table 1: Comparison of the effects of three filtering algorithms

Filtering algorithm	MSE
adaptive filtering	0.014189
Kalman filtering	0.025751
FIR filtering	0.025127

5. Conclusion

Compared with Kalman filtering and FIR filtering algorithms, the adaptive algorithm can adjust the filtering mechanism according to the changes of external noise and interference, so it has a wider range of applicable scenarios, and the adaptive algorithm can have a better filtering effect in the face of a more complex environment. The adaptive filtering algorithm first initializes the filter order, step size and coefficients, and creates a space to store the filtered signal. Then, the algorithm iterates from a specific position of the noise signal, each time extracting the current and previous samples to form the input vector, calculating the predicted output and comparing it with the current sample of the original signal to obtain the error value. Then, based on the least mean square algorithm, the filter coefficients are adjusted with the error value, step size and input vector, and the predicted output is deposited into the corresponding space. After completing the iterations, the algorithm calculates the mean square error to evaluate the effect [15][16].

However, adaptive filtering also exposes certain limitations while showing its excellent filtering function. On the one hand, with the increase of the order of adaptive filtering, i.e., the number of signal samples considered and the number of iterations, the adaptive filter with high order and high number of iterations may consume more computational resources, storage resources, etc., than other filtering algorithms, and a large number of matrix operations and data processing require high-performance processors to support. On the other hand, the choice of step size is a major problem for adaptive filtering algorithms, a larger step size can accelerate the convergence speed, but at the same time it will also make the system stability worse, easy to produce certain fluctuations in the filtering process, and even deviate from the true value; smaller step size can ensure stability, but it makes the convergence process seem long, and real-time performance is reduced.

Therefore, in the future development of adaptive filtering, when researching low - complexity algorithms, we should optimize the algorithm structure and adopt new computational methods and data - processing techniques to reduce unnecessary computational steps and resource consumption. In the optimization of the convergence mechanism, the same adaptive advantage should be played, synchronously updating the step size in response to the changes in noise and signal to achieve a balance between stability and convergence speed.

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