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Near-Real-Time Detection of Pulse Oximeter PPG Peaks Using Wavelet Decomposition ⋆

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Abstract:
Pulse oximeters are frequently used to provide real time measurements of heart rate and blood oxygen saturation (SpO_2). SpO_2 is calculated by taking the ratio of the AC to DC components of the photoplethysmograph (PPG) signal measured by the pulse oximeter. For accurate estimation of SpO_2, the AC component needs to be extracted from the signal through signal processing, where accurate peak detection is a crucial, difficult element. This paper investigates the use of the wavelet transform for real time signal processing to detect peaks that could be unintentionally attenuated through more conventional filtering methods. Four mother wavelets (Daubechies 3, symlets 2, coiflets 3 and reverse biorthogonal 1.5) were tested against each other to determine the wavelet with the best representation of the PPG signal in a noisy environment (SNR of 6.44). The reverse biorthogonal (rbio1.5) mother wavelet was found to better represent the PPG signal with a specificity of 0.97 and a sensitivity of 0.97. Further research into the decomposition depth of the rbio1.5 wavelet resulted in an optimal depth of 3, with the 2^{nd} and 3^{rd} levels being used for reconstruction of the signal. Using a wavelet length of 128 samples resulted in a time delay of 2.56 seconds. This time delay is well within clinical requirements for near real-time-signal analysis involving these devices.

Keywords: Digital signal processing, PPG signal, discrete wavelet transform, mother wavelet, filters

1. INTRODUCTION

Pulse oximeters are used in a number of situations to non-invasively measure the heart rate and blood oxygen level (SpO_2) of patients (Ortega et al., 2011). The algorithm used to estimate SpO_2 requires accurate measurement of the signal generated by the pulse oximeter. This paper explores the analysis of the photoplethysmograph (PPG) signal through near-real-time wavelet decomposition and the choice of the appropriate mother wavelet.

Pulse oximeters use red and infrared LEDs and a photodetector placed on the skin to produce PPG signals. The LEDs and photodetector are typically placed on either side of a finger, with the photodiode measuring the intensity of the transmitted light. As blood pulses through a finger, the amount of absorbed light varies. The fluctuating PPG signal is indicative of changes in blood volume, as well as the oxygen saturation in the blood (Allen, 2007; Daly and Leahy, 2013). Oxygenated haemoglobin absorbs infrared light better than red light and de-oxygenated haemoglobin absorbs red light better than infrared light (Khan et al., 2017). The ratio of these detected intensities thus gives the oxygen concentration in the blood.

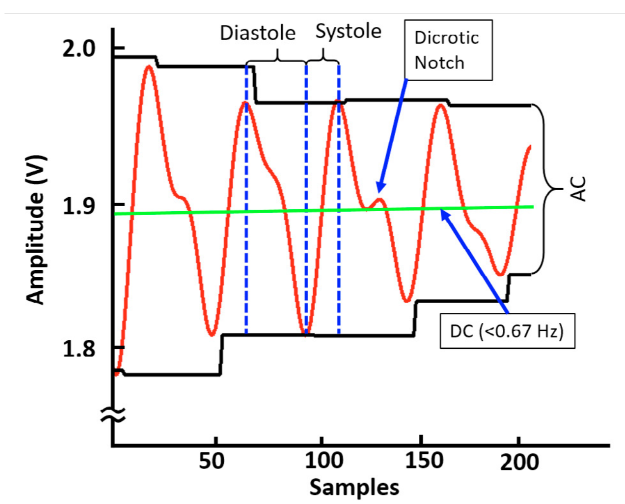

Fig. 1. Photoplethysmograph waveform filtered with a 10 Hz lowpass Chebyshev FIR filter.

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To calculate the ratio of red to infrared light, the amplitude of absorbed light must be extracted from the raw PPG signal. The AC component of the signal is associated with the pulsatile blood and the DC component is associated with all non-pulsatile tissue such as skin and bone. Equation 1 gives the ratio of ratios used to estimate SpO_2, where suffixes r and ir represent measurements using red and infrared lights respectively.

$$R = \frac{AC_r/DC_r}{AC_{ir}/DC_{ir}} \tag{1}$$

Figure 1 shows a typical PPG signal, where the pulse wave is the complete cycle between the systole and diastole of the cardiac cycle. Present in the diastolic phase is the dicrotic notch, an increase in blood volume resulting from a pressure wave reflection at bifurcations of the arterial tree (Sherebrin and Sherebrin, 1990). The peaks and troughs of the signal must be correctly identified to accurately estimate SpO_2. False peaks and troughs, such as the dicrotic notch introduce large errors into the calculation due to incorrectly estimated amplitudes, especially since the peaks of the PPG waveform can consist of less than 1% of the signal (Mendelson, 1992). Thus, filtering is required to extract the correct AC amplitude.

Estimation of the AC amplitude is essential to the calculation of SpO_2. Conventionally, methods such as a bandpass filter have typically been used to extract the AC component (Khan et al., 2015; Aboy et al., 2005). However, these methods tend to truncate the peaks, impacting results.

This paper investigates the use of wavelet decomposition to de-noise the raw data to accurately track the peaks and troughs of the PPG signal. A previous paper used wavelet decomposition to de-noise synthetic PPG data (Joseph et al., 2014). An additional paper by Li et al. (2017) developed a hybrid wavelet decomposition method for PPG peak detection. Both papers applied the wavelets through post processing. Thus, while these papers show the usefulness of the wavelet transform in PPG analysis, the wavelet transform is yet to be implemented in real time.

Where the Fourier Transform uses the sum of sines and cosines to represent the signal, wavelet transforms use a fixed function called a mother wavelet. The choice of mother wavelet allows different features of the signal to be extracted. Wavelets represent the signal as a combination of scaling and wavelet functions. The scaling functions provide an overview of the signal, while the wavelets represent the finer details at various scales (Lee and Yamamoto, 1994). The combination of the coarse signal with the details provide a multi-resolution analysis of the signal. In this paper, the Daubechies, symlets, coiflets, and reverse biorthogonal wavelet families are investigated for their ability to track the PPG signal.

2. METHODS

The algorithm used to detect peaks and troughs has been adapted from work by Karlen et al. (2012) who used an adaptive algorithm that uses changes in gradient direction to indicate peaks and troughs. This method works well at detecting the signal through motion artefacts. However, the signal used in this paper has a high noise level consisting of many false peaks and troughs, so filtering is required to remove them.

The DWT is used to obtain near-real-time analysis of the signal by analysing the signal in segments (Goelz et al., 2000). The DWT runs through multiple levels of decomposition, at each stage the length of the signal vector is halved, leaving the high and low frequency components of the signal. Table 1 shows the decomposition levels of the wavelets used in this paper. As the sample rate of the system is 50 Hz, the highest possible frequency component of the signal is 25 Hz.

Table 1. Frequency decomposition using the DWT

Level	Filter	Frequency Range(Hz)	Data Length
1	High	12.5 - 25	64
	Low	0 - 12.5	64
2	High	6.25 - 12.5	32
	Low	0 - 6.25	32
3	High	3.125 - 6.25	16
	Low	0 - 3.125	16

To minimise the time delay caused by the block method of wavelet analysis, a buffer size of 128 was used. With a sample rate of 50 Hz, the time delay is 2.56 seconds. This time delay was in a clinical context, deemed sufficiently responsive for use in near real time as change of patient condition is negligible over such a short time frame. Once the wavelet has filtered the 128 samples, the buffer is passed into the peak and trough detection algorithm.

3. CHOICE OF MOTHER WAVELET

Four mother wavelets were investigated for use in signal analysis (Daubechies, symlets, coiflets and reverse biorthogonal). The wavelets were chosen on accuracy of signal reconstruction and removal of false peaks from the signal. As the analysis is in real time, the length of the mother wavelet is kept as short as possible to reduce computation time. The scaling and wavelet functions for each mother wavelet are shown in Figure 2.

3.1 Daubechies

Of the Daubechies mother wavelets family, the Daubechies 3 wavelet was chosen because the mother wavelet closely represents the typical PPG waveform. The large rise, subsequent drop and smaller rise mimic the dicrotic notch present in the signal. Daubechies wavelets extend the base Haar wavelet by using longer filters, which produce smoother scaling functions and wavelets.

3.2 Coiflets

Coiflets were designed as an extension of the Daubechies wavelets with the purpose of maintaining a close match between the raw signal and the calculated trend values. For an analog signal, such as the PPG waveform, the coiflet transform produces a much closer match between subsignals and the raw signal compared to the Daubachies transforms (Meyer, 2008).

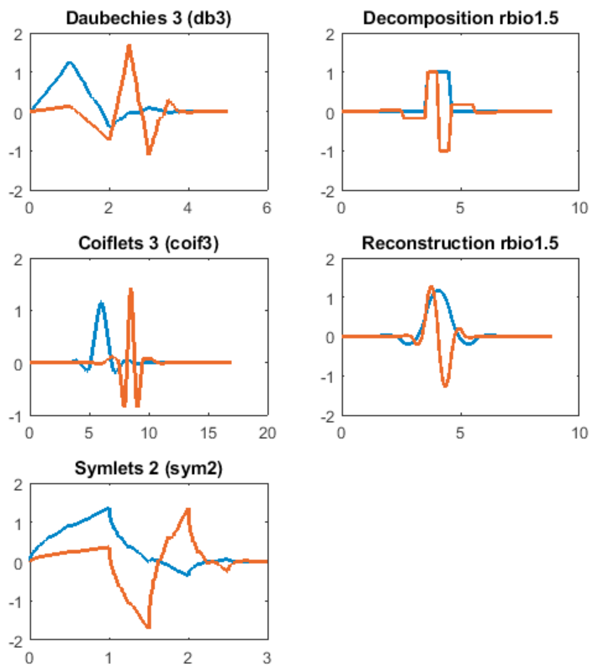

Fig. 2. Wavelet (orange) and scaling (blue) functions for each mother wavelet tested.

3.3 Symlets

Symlets are nearly symmetrical modifications to the Daubechies family. They give the wavelets near linear phase response. Other than the increased symmetry, the symlet family is similar to the Daubechies family of wavelets.

3.4 Biorthogonal

The biorthogonal family of wavelets exhibit linear phase, which is needed for accurate signal reconstruction. The biorthogonal wavelets differ from the Daubechies family and subfamilies due to having different decomposition and reconstruction wavelet functions as shown in Figure 2. The reverse biorthogonal wavelet uses the corresponding reconstruction wavelet as the decomposition and the decomposition wavelet for reconstruction. This characteristic gives the reverse biorthogonal wavelets interesting properties, such as rbio1.5 used in this research, which uses a square wave to decompose the signal, but a curved wavelet for reconstruction.

4. PEAK AND TROUGH DETECTION

For estimation of SpO_2, the AC component of the signal (frequencies 0.67-4.5 Hz) needs to be precisely isolated from the DC component (frequencies $<$ 0.67 Hz). Hence, the amplitude of the AC component must be calculated from the corresponding peaks and troughs. The algorithm used to measure the beat to beat peaks and troughs was adapted from the adaptive thresholding method proposed in Karlen et al. (2012). The algorithm uses the steps shown in Table 2, where x is the new data point.

The linear least squares method is used to calculated the gradient of the signal. Taking the filtered gradient over 5 previous values reduces the influence of outliers and small point to point changes in gradient. A sign change in gradient indicates that a peak (+ve to -ve) or a trough (-ve to +ve) has been found.

Table 2. Peak and Trough Detection Algorithm.

```
data_buffer = [0, 0, 0, 0, 0], T_amp = [0, 1]
grad, current_grad, amp = 0
while 1:
    data_buffer[i] = x
    grad = least_squares(data_buffer) # get the gradient.
    if grad < 0 and current_grad > 0: #peak
        amp = x - prev_trough
        if within_tol(amp, T_amp): # acceptable amp
            T_amp = [(0.95×T_amp[0] + amp × 0.60)/2,
                    (1.2×T_amp[1] + amp × 1.2)/2]
            peak_found = True
            current_grad = grad
        else: # Expand the tolerance
            T_amp = [0.5×T_amp[0], 1.5 ×T_amp[1]]
    if grad > 0 and current_grad < 0: #trough
        amp = x - prev_trough
        if within_tol(amp, T_amp): # acceptable amp
            T_amp = [(0.95×T_amp[0] + amp × 0.60)/2,
                    (1.2×T_amp[1] + amp × 1.2)/2]
            trough_found = True
        current_grad = grad
        else: # Expand the tolerance
            T_amp = [0.5×T_amp[0], 1.5 ×T_amp[1]]
    i += 1
    if i >= length(data_buffer):
        i = 0
```

A tolerance value is used to determine if a detected peak or trough is at an allowable amplitude. Using an amplitude tolerance based on the previous amplitudes allows adaptive control over tolerances. If an amplitude is outside the acceptable range, the tolerance is widened. Each successful peak detection reduces the tolerance, meaning the algorithm can converge to any amplitude from start up. To ensure fast conversion, tolerance expansion and contraction is proportional to the error between the tolerance and calculated amplitude. The signal to noise ratio (SNR) of each wavelet was calculated by taking the RMS of the raw non-pulsatile and filtered pulsatile signal

5. EXPERIMENTAL VALIDATION

The PO system is based on the CY8CKIT-050 PSoC 5LP Development Kit (Cypress Semiconductor, San Jose, CA, USA) employing an ARM Cortex M3 microcontroller. The sensor is a Nelcor Pulse Oximeter (model: 302701001, Biometric Cables, Guindy, Chennai, India) attached to an in-house sensor driver. The raw data from the sensor is sent via serial at 50 Hz to an Intel NUC running Ubuntu 16.04 LTS on an Intel Celeron processor with 4 GB of ram. A GUI has been designed to display the data in raw, FIR filtered and wavelet filtered real time graphs. The software used for wavelet analysis is PyWavelets v0.502 (Lee et al., 2006).

5.1 Performance Assessment

For analysis of each wavelet, 10 minutes of live PPG data was recorded from a 23 year old male sitting at rest. Over the 10 minutes of recorded data, 660 peaks were detected by an independent expert. The data set contains motion artefacts and sections of high noise (SNR 5.13). The data is analysed individually for each wavelet to generate a confusion matrix. As well as the accuracy of peak detection, the wavelets are compared to each other on beat to beat basis. Finally, results were compared to a typical commercially used bandpass filtered approach.

The specificity and sensitivity of peak detection for each wavelet was also calculated. A true positive (TP) is classed as a pulse with both the peak and trough correctly identified, false positive (FP) is the incorrect detection of a peak or trough causing incorrect amplitude estimation. False negatives (FN) occur when either the peak or trough has not been identified. True negative is not used in this analysis as correctly identifying when there is no peak is not viable with continuous heart beats. The signal to noise ratio (SNR) of each wavelet was calculated by taking the RMS of the raw non-pulsatile and filtered pulsatile signals.

6. RESULTS

Each of the four mother wavelets were compared to each other to determine the wavelet to continue development with. Figure 4 displays the response of each wavelet to the same raw data. Each mother wavelet was tested at the decomposition level with the fewest false peaks generated upon reconstruction. The rbio1.5, coif3 and the Db3 mother wavelets were reconstructed with the 2^{nd} and 3^{rd} level, whereas sym2 was reconstructed with just the 2^{nd} level as only two levels of decomposition could be achieved at a buffer size of 256 samples.

Table 3. SNR of each reconstructed signal.

	Coiflet 3	Rbio 1.5	Symlets 2	Daubechies 3
SNR (dB)	6.63	6.44	5.13	6.44

The raw pulsatile and non-pulsatile are shown in Figure 3. The non-pulsatile component of the signal was obtained by temporarily occluding blood-flow to the finger. Table 3 gives the SNR for each wavelet, calculated from the reconstructed signal from each wavelet run over the raw data.

Table 4. Results of the confusion matrix

Method	TP	FP	FN	Specificity	Sensitivity
Coif3	609	26	23	0.96	0.96
Db3	613	19	24	0.97	0.96
Sym2	611	19	24	0.97	0.96
Rbio1.5	610	22	21	0.97	0.97
Bandpass	429	232	11	0.65	0.98

The results generated by the confusion matrix produced from testing is given in Table 4. Each wavelet performed similarly, with good specificities and sensitivities. Coif3 was found to have the most false positives, resulting in a lower specificity. The rbio1.5 wavelet has the highest sensitivity than the other three wavelets with a value of 0.97. A 0.67-4.5 Hz IIR bandpass filter was also tested against the data. The typically used band-pass filter performed poorly as the dicrotic notch would be frequently be detected as a trough.

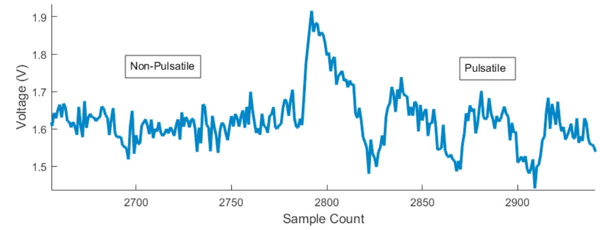

Fig. 3. Pulsatile and non-pulsatile PPG signal used to calculate the SNR

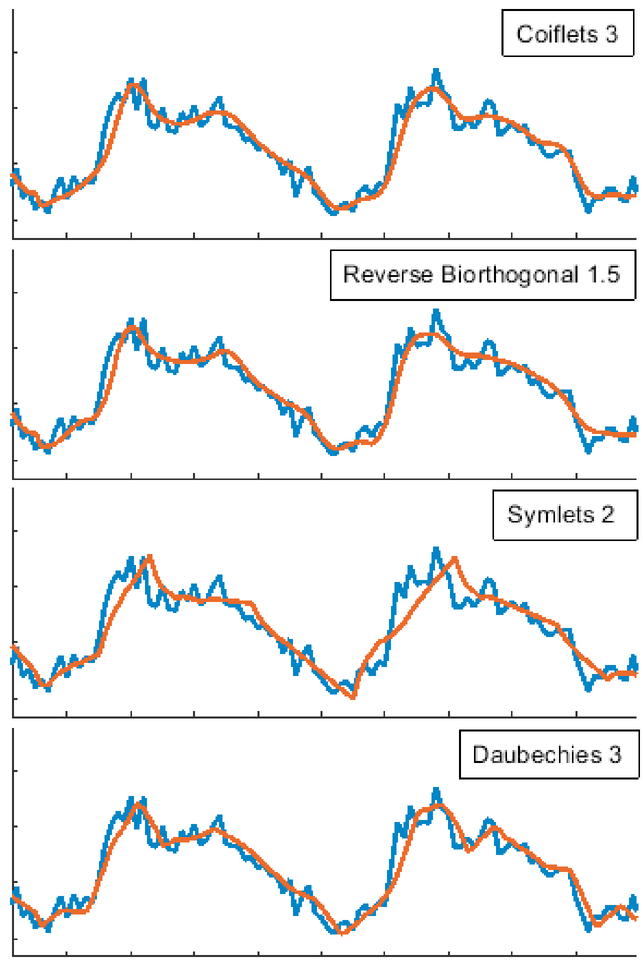

Fig. 4. Comparison between each reconstructed signal (red) to the raw data (blue).

6.1 Comparison of Wavelet Response

As discussed earlier, the coiflets 3 wavelet decomposition closely tracks the raw data. This tracking is helpful in obtaining close representation of the peaks and troughs. While the peaks and troughs of the signal are accurately preserved, this close representation leads to additional turning points being detected, such as the trough in the second pulse. A higher amount of false positives shows the effect of introducing these additional turning points.

The reverse biorthogonal 1.5 wavelets decompose the signal with a square wave. On reconstruction, the wavelet used is rounded. This behaviour results in the rounded tracing of the output. Due to the linear phase delay, the peaks and troughs of the filtered data are spaced at the

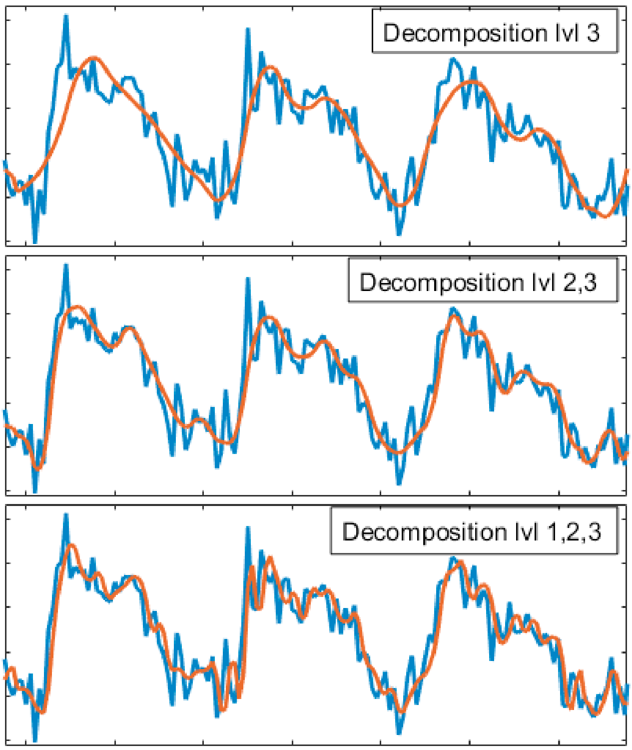

Fig. 5. The effect of rbio1.5 decomposition levels on signal reconstruction

same distance as the raw data. The dicrotic notch in the first pulse is accurately detected and the second pulse has a flattened dicrotic notch.

The sharp shape of the symlets 2 mother wavelet results in clear turning points at the systolic and diastolic peaks, but do not represent a PPG signal in shape. The dicrotic notch in the first pulse is flattened and the second pulse shows no dicrotic pulse. While the peak and trough values track the amplitudes of the raw data, the peaks are time delayed, resulting in inaccurate heart rate calculation.

The Daubechies 3 wavelet has a response similar to the coiflet, where the raw signal is closely matched by the filtered data. However, the peaks and troughs of the signal are not rounded. The position of the peaks and troughs map to the maximum and minimum values of the raw data. This leads to errors in detection as any noise at the turning points will result in a false amplitude detection.

6.2 Further Analysis of rbio1.5

The wavelet chosen for further analysis was rbio1.5. This wavelet was chosen due to the linear phase, increased sensitivity, close representation of the data without additional turning points, and rounded peaks and troughs.

To further analyse the rbio1.5 wavelet, the three levels of decomposition used were plotted in Figure 5. At the 3^{rd} level of decomposition, frequencies below 3.125 Hz are retained. As the heart rate during testing was 1 Hz (60 BPM), both the fundamental frequency and dicrotic notch are present in the filtered signal. However, the rise between the diastolic and systolic phase is too sharp to be accurately tracked by this frequency range.

Using all three levels of decomposition does not remove sufficient noise from the signal to detect peaks and troughs. Thus, the first frequency range (12.5-25 Hz) is removed from the data reconstruction. The decomposition level used for analysis is the combination of the 2^{nd} (3.125-6.25 Hz) and 3^{rd} decomposition levels. This filter follows the sharp rise from trough to peak, while reducing the amount of false peaks and troughs.

Figure 6 plots the output from the near-real-time peak and trough detection algorithm. The wavelet output closely follows the raw data with only the high frequency peaks and troughs not closely followed. The SNR of the raw signal is very low (6.44 dB), so additional peaks and troughs are expected to be detected. The peak and trough detection algorithm displays the detected turning points. The update on amplitude detection is delayed due to the nature of the detection algorithm.

7. DISCUSSION

Four different mother wavelets were tested for suitability of PPG signal analysis. A low sample rate of 50 Hz and the requirement for a minimal time delay resulted in a buffer length of 128 samples used for each wavelet decomposition. Such a small wavelet length reduces the levels of decomposition available. However, it was deemed an acceptable depth as the desired signal frequencies occur below 3.125 Hz.

The four mother wavelets gave different characteristics of decomposition. A typical PPG waveform does not contain sharp edges as arteries do not produce immediate changes in blood volume. The symlets wavelet was the least accurate in both time resolution and close representation of the signal due to its sharp edges. As both the coiflets and Daubechies wavelets followed the signal too closely false turning points were introduced. This is important as it causes false positives in detection. It is better for the signal to miss a good beat than incorrectly identify a peak or trough, which greatly affects the heart rate or SpO_2.

To reduce the chance of error in peak and trough detection, the output from the wavelet should have minimal false turning points. However, if the amplitude tolerance is decreased to avoid false turning points such as the dicrotic notch, the risk of missing actual peaks or troughs increases. As shown in Figure 6, the AC amplitude can vary greatly from peak to peak, requiring a wide amplitude tolerance.

The raw data used in this paper has a low signal to noise ratio (6.44 for rbio1.5), but still gives good specificity and sensitivity results. Use of the wavelet transform on less noisy signals may allow wavelets such as coiflets 3 to be used as fewer false peaks and troughs would be present. Thus, the rbio1.5 mother wavelet is recommended for noisy signals, so signals with a higher SNR may benefit from other wavelets such as the coiflet family.

Other papers investigating the use of wavelets for PPG analysis have done so in post processing and at higher sampling rates. This choice allows a greater depth of decomposition, but at the cost of computation requirements. An improvement to the current system would be to increase the sample rate so a greater decomposition depth can be reached. If the depth can reach below 0.67 Hz (>5

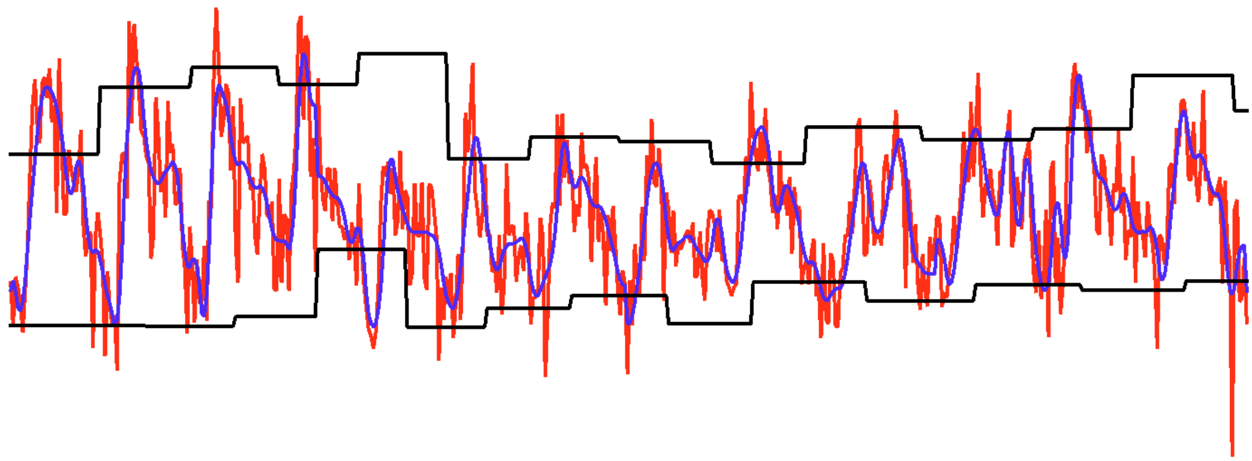

Fig. 6. Peak and trough detection from the rbio1.5 (blue) filtered raw (red) data with the detected peak and troughs (black)

levels), then the DC component can be considered to be the approximation waveform. Calculating both the DC and AC components would allow SpO_2 to be calculated solely from a single wavelet decomposition as currently, a 0.67 lowpass filter is required to obtain the DC component.

8. CONCLUSIONS

This paper investigated wavelet transforms for use in near real time PPG peak and trough detection. Four mother wavelets were tested to determine the wavelet which best represents the PPG signal. A wavelet length of 128 samples gives a clinically acceptable time delay of 2.56 seconds. Of the four wavelets tested, the reverse biorthogonal 1.5 (rbio1.5) mother wavelet was the most suited to PPG signal analysis with a specificity of 0.97, a sensitivity of 0.97 and an SNR of 6.44. The Daubechies and coiflet wavelets introduced additional peaks and troughs to the signal, resulting in reduced specificity (0.97). The use of symlets to analyse the signal resulted in sharp peaks and troughs that did follow the raw data in time resolution.

Further analysis of the rbio1.5 wavelet decomposition levels gave the best results with a reconstruction of the 2^{nd} (3.125-6.35 Hz) and 3^{rd} (0-3.125 Hz) decomposition levels. An increase in sample rate would allow greater decomposition depth, allowing both the AC and DC components of the signal to be calculated in the same decomposition. Overall, the wavelet decomposition yields an accurate AC amplitude measurement, with an increase in sample rate needed to take full advantage of the wavelets used.

REFERENCES

Aboy, M., McNames, J., Throng, T., Tsunami, D., Ellenby, M.S., and Goldstein, B. (2005). An automatic beat detection algorithm for pressure signals. *IEEE Transactions on Biomedical Engineering*, 52(10), 1662–1670.

Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. *Physiological Measurement*, 28(3), R1–R39.

Daly, S.M. and Leahy, M.J. (2013). Go with the flow: A review of methods and advancements in blood flow imaging. *Journal of Biophotonics*, 6(3), 217–255.

Goelz, H., Jones, R.D., and Bones, P.J. (2000). Wavelet Analysis of Transient Biomedical Signals and Its Application to Detection of Epileptiform Activity in the ECG. *Clinical Electroencephalography*, 31(4).

Joseph, G., Joseph, A., Titus, G., Thomas, R.M., and Jose, D. (2014). Photoplethysmogram (PPG) signal analysis and wavelet de-noising. In *Emerging Research Areas: Magnetics, Machines and Drives (AICERA/iCMMD), 2014 Annual International Conference on*, 1–5. IEEE.

Karlen, W., Ansermino, J.M., and Dumont, G. (2012). Adaptive pulse segmentation and artifact detection in photoplethysmography for mobile applications. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 3131–3134. IEEE.

Khan, M., Pretty, C., Amies, A., Elliot, R., Shaw, G., and Chase, G. (2015). Investigating the Effects of Temperature on Photoplethysmography.

Khan, M., Pretty, C.G., Amies, A.C., Balmer, J., Banna, H.E., Shaw, G.M., and Chase, J.G. (2017). Proof of concept non-invasive estimation of peripheral venous oxygen saturation. *Biomedical engineering online*, 16(1), 60.

Lee, D.T. and Yamamoto, A. (1994). Wavelet analysis: theory and applications. *Hewlett Packard journal*, 45, 44–44.

Lee, G., Wasilewski, F., Wohlfahrt, K., O'Leary, A., and Nahrstaedt, H. (2006). PyWavelets - Wavelet Transforms in Python.

Li, S., Jiang, S., Jiang, S., Wu, J., Xiong, W., and Diao, S. (2017). A Hybrid Wavelet-Based Method for the Peak Detection of Photoplethysmography Signals. *Computational and Mathematical Methods in Medicine*, 2017, 1–8.

Mendelson, Y. (1992). Pulse oximetry: theory and applications for noninvasive monitoring. *Clinical Chemistry*, 38(9), 1601–1607.

Meyer, Y. (2008). Daubechies Wavelets. In *A primer on wavelets and their scientific applications*. CRC Press.

Ortega, R., Hansen, C.J., Elterman, K., and Woo, A. (2011). Pulse oximetry. *N Engl J Med*, 364, 33–6.

Sherebrin, M.H. and Sherebrin, R.Z. (1990). Frequency analysis of the peripheral pulse wave detected in the finger with a photoplethysmograph. *IEEE Transactions on biomedical engineering*, 37(3), 313–317.