УДК 611.131

ADAPTIVE DE-NOISING IN ARTERIAL PULSE WAVE BASED ON LIFTING SCHEME DISCRETE WAVELET

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Abstract. Pulse wave denoising is an essential procedure in pulse wave analysis. Lifting wavelet denoising speeds up the typical wavelet denoising, and is thus of great interest. Three groups (five each) of data sets (radial pulse waves recorded from healthy subjects and sphygmogram and plethysmogram obtained from the Multi-parameter Intelligent Monitoring in Intensive Care database) were enrolled for this study. The predictor of the lifting scheme were adaptively calculated using the Least Mean Square (LMS) algorithm. Comparison analysis were applied with the typical wavelet denoising and adaptive denoising using typical wavelet. The adaptive denoising algorithm using lifting scheme can effectively eliminate the noise in pulse wave signal (*MSE* is 0.0469, 0.0256, 0.0147, 0.0088, 0.0051 and 0.0035, respectively when the *SNR* of the pulse signal equals 5, 10, ⋯, 30db). As the *SNR* gets higher, the performance of the adaptive denoising algorithm using lifting scheme gets closer to those of the typical wavelet denoising and adaptive denoising algorithm using typical wavelet (*MSE* of the lifting scheme denoising algorithm and the other two typical algorithms, 0.0035, 0.0036 and 0.0084, respectively, with *SNR* of the raw pulse signal 30db).
Keywords. Pulse wave, lifting scheme, LMS

1. Introduction

Cardiovascular diseases are the leading cause of death around the word (Alwan 2014).Pulse wave reflects the status of cardiovascular system (Daubechies and Sweldens 1998, Sweldens 1996). However, Arterial pulse signal is always corrupted with interference generated by respiration, motion artifacts, and the electromagnetic environment, which lead to inaccuracies in pulse wave acquisition and even affect further analysis. Thus denoising approaches are essential in pulse wave acquisition and analysis.

The frequency bands of respiration interference and motion artefacts are close to that of the pulse wave. They change the baseline and the shape of the pulse wave, making it inappropriate for classical filtering methods.

Wavelet decomposition, as a way of multi-resolution analysis, shows good performance in extensive range of applications including pulse wave denoising. Zhao et al(2013)applied wavelet decomposition on the noise reduction and feature point identification of pulse wave signals; Fedotovet al(2015)further studied the wavelet denoising method, focusing on the optimally chose of the parameters.

However, as the typical wavelet is based on Fourier transform, complex mathematical computation is required. Compared with typical wavelet, lifting scheme is a much simpler way to implement wavelet decomposition without Fourier transform. Lifting scheme was first proposed by Sweldens (1996) to fast construct compactly supported wavelets with compactly supported duals. It gives the user full control over the freedom remaining after fixing the biorthogonality relations, so that One can custom design a wavelet for a particular application. Daubechies and Sweldens(1998), proved that all typical wavelets can be described by the lifting scheme.

Wavelet basis selection depends on the signal itself and the purpose and thus is always one of the key researches in wavelet analysis. Least Mean Squares (LMS)(Widrowet al 1975, Widrow et al 1976)is an adaptive algorithm to find the coefficients of a system by producing the least mean squares of the difference between the desired output and the actual output. Liu(2013) applied the LMS method on lifting wavelet designing for background correction of analytical signals.

This study aims to propose a method for pulse wave denoising based on lifting wavelet and LMS. The following of this paper is organized as: Section 2 includes the implementation of the adaptive denoising algorithm using lifting scheme and comparison analysis among the adaptive denoising algorithm using lifting scheme, the typical wavelet denoising algorithm and the adaptive denoising algorithm using typical wavelet; Section 3 and 4 shows and discusses the results of section 2, respectively.

2. Methods

2.1 Data Collection

To test the reliability of this method, three groups (five each) of data sets were enrolled for this study as shown in table 1.The first is radial pulse waves (No. 1-5 in table 1) obtained from five subjects using a pressure sensor. The acquisition equipment was BL-420Sbiological functional experimental system (Chengdu Taimeng Software Co.LTD, China) with a sampling frequency of 1KHz.The other two kinds of data were sphygmogram and plethysmogram (No. 6-10 and 11-15, respectively, table 1), five each, obtained from the Multi-parameter Intelligent Monitoring in Intensive Care (MIMIC) database (Moody and Mark 1996).The sampling frequencies were both 125Hz.For the convenience of further analysis, data in the three groups were all resampled to 100Hz.

Table 1. Details of data sets[a].

No.	Sex	Age (y)	Diagnostic	Data acquisition
1	M	25	Healthy	A
2	M	28	Healthy	A
3	F	28	Healthy	A
4	F	23	Healthy	A
5	M	23	Healthy	A
6	M	70	Bleed	A
7	M	38	Respiratory failure	P
8	M	80	Bleed	P
9	F	67	Respiratory failure	A
10	F	82	CHF /Pulmonary edema	A
11	F	63	MI/Cardiogenic shock	P
12	M	68	Angina	A
13	M	48	MI/arrest	A
14	M	75	Respiratory failure	P
15	M	78	Sepsis	A

[a] Data collection method: A represents sphygmogram, P represents plethysmogram.

2.2 Lifting wavelet

As shown in figure 1, the lifting wavelet transform consists of the following three steps:

- Split. Split the signal X into two disjoint sets which are called the polyphase components: the evens $X_e = (X_{2k})$, $k \in Z$, and the odds $X_o = (X_{2k}+1)$, $k \in Z$.
- Predict. Build a predictor P to predict one set, e.g. the evens, using another. Then, the details, difference between the predicted and the original set, d is

$$d = X_e - P\left(X_o\right) \quad (1)$$

- Update. Replace the evens with smoothed values s with the use of an update operator U applied to the details d:

$$s = X_e + U(d) \tag{2}$$

All of the previous three steps are invertible, which means that one can recover the raw signal X and the sets X_e and X_o from d and s.

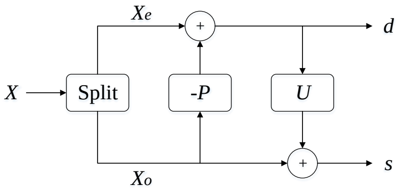

Figure 1. Block diagram of the lifting scheme (Daubechies and Sweldens 1998).

2.3 Determination of decompositionlevel

In discrete wavelet analysis, the noise is distributed mainly in lower levels, while the desired signal in higher levels. Thus, with the increase of decomposition level, the high-frequency coefficients changes in three stages:

- At a lower decomposition level, the high-frequency coefficients mainly reflect the noise amplitude. At this stage, the variance of the high-frequency coefficients rapidly decreases with the increase of the decomposition level.
- The high-frequency coefficients decreases to minimum as decomposition level increases to K.
- As decomposition level continues to increase upon K, the high-frequency coefficients rapidly increases for it mainly reflects the distribution the desired signal at this decomposition level.

According to this feature, the variance of the high-frequency coefficients at different levels were calculated, as shown in figure 2, so that the appropriate decomposition level K=3can be determined by the minimum of the variance of the high-frequency coefficients.

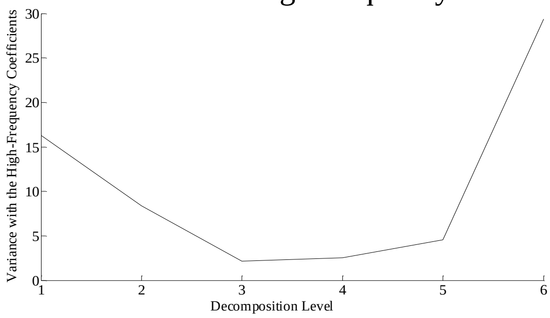

Figure 2. Variance of the high-frequency coefficients.

2.4 Predictor design based on LMS

In this study, the predictor P was designed adaptively using the Least Mean Square (LMS) algorithm, which was developed by Widrow *et al* (1975, 1976)as an adaptive gradient search algorithm. The flow chart of P-calculation is shown in figure 3.

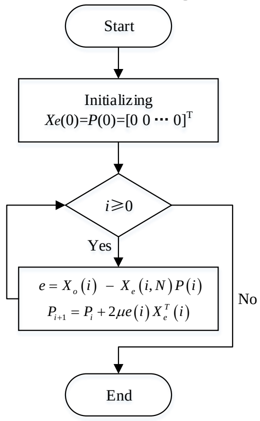

Figure3. Flow chart of LMS algorithm.

The construction of Pin the LMS method is to minimize the error

$$e = X_o(i) - X_e(i,N)P(i) \tag{3}$$

where $P(i)$ is the predictor of length N, $X_e(i,N)$ represents the nearby N points of $X_e(i)$. P is updated at each step by (Widrow *et al* 1976)

$$P_{i+1} = P_i + 2\mu e(i) X_e^T(i) \tag{4}$$

Then P can be derived from an iteration of equation (3) and (4).

2.5 Evaluation criteria

To evaluate the performance of the adaptive denoising method, the following four criteria were used:

- Signal-to-Noise Ratio (SNR) defined as energy ratio of the desired signal to the background noise and is defined as

$$SNR = 10\lg \frac{\sum_{i=1}^{m} S_r^2(i)}{\sum_{i=1}^{m} n^2(i)} \tag{5}$$

where S_r is the raw pulse signal.

- Mean Square Error (MSE): measures the difference between the raw signal and the denoised signal and is calculated as

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{m}[S_d(i) - S_r(i)]^2} \tag{6}$$

where S_d indicates the denoised signal

- Correlation Coefficient (ρ) illustrates the correlation between the raw signal and the denoised signal and is calculated as

$$\rho = \frac{\sum_{i=1}^{m} S_r(i) S_d(i)}{\sqrt{\sum_{i=1}^{m} {S_r}^2(i)}\sqrt{\sum_{i=1}^{m} {S_d}^2(i)}} \tag{7}$$

- Signal-to-Distortion Ratio (SDR) is a quality measure that reflects the distortion and is defined as

$$SDR = \frac{\sum_{i=1}^{m}[S_d(i) - S_r(i)]^2}{\sum_{i=1}^{m} {S_r}^2(i)} \tag{8}$$

2.6 Comparative analysis

To evaluate the performance of the adaptive denoising algorithm using lifting scheme, comparison with the typical wavelet denoising and adaptive denoising using typical wavelet were displayed.

To study this comparison with the change of the noise, white noises were quantitatively added to the pulse wave signals. The four evaluation criteria, *SNR*, *MSE*, *a*nd *SDR*, were used to determine the appropriate wavelet basis. Table 2 is the performance of lifting wavelet denoising with different basis applied on signals of different *SNR*. The lifting wavelet denoising shows better performance when applied to signals with larger *SNR*. And lifting wavelet denoising with 'db4' basis shows higher MSE and *SNR*, and lower ρ. Thus, 'db4' basis was chosen. In adaptive denoising using typical wavelet, the pulse signal was segmented and the appropriate wavelet bases were chosen by the minimum MSE for each single segment.

Table 2. Results of the denoised signal in different wavelet base functions decomposed in 3 levels.

Basis \ SNR (MSE/ρ/SDR)	5db	10db	15db	20db	25db	30db
haar	0.3673 /0.5000 /2.9458	0.2090 /0.7154 /0.9534	0.1165 /0.8787 /0.2963	0.0670 /0.9543 /0.0980	0.0395 /0.9834 /0.0340	0.0214 /0.9950 /0.0100
db2	0.0603 /0.9622 /0.0793	0.0347 /0.9871 /0.0263	0.0193 /0.9960 /0.0081	0.0113 /0.9986 /0.0028	0.0067 /0.9995 /0.0010	0.0046 /0.9998 /0.0005
db3	0.0925 /0.9170 /0.1869	0.0547 /0.9689 /0.0654	0.0300 /0.9903 /0.0197	0.0173 /0.9967 /0.0066	0.0104 /0.9988 /0.0024	0.0064 /0.9996 /0.0009
db4	0.0438 /0.9795 /0.0419	0.0243 /0.9936 /0.0129	0.0138 /0.9979 /0.0042	0.0084 /0.9992 /0.0015	0.0049 /0.9997 /0.0005	0.0036 /0.9999 /0.0003
db5	0.0442 /0.9791 /0.0426	0.0246 /0.9935 /0.0132	0.0138 /0.9979 /0.0042	0.0084 /0.9992 /0.0015	0.0050 /0.9997 /0.0005	0.0036 /0.9999 /0.0003
db6	0.0478 /0.9757 /0.0499	0.0272 /0.9921 /0.0161	0.0162 /0.9971 /0.0058	0.0107 /0.9987 /0.0025	0.0076 /0.9994 /0.0013	0.0064 /0.9995 /0.0009
db7	0.0443 /0.9790 /0.0428	0.0244 /0.9936 /0.0130	0.0140 /0.9979 /0.0043	0.0085 /0.9992 /0.0016	0.0052 /0.9997 /0.0005	0.0036 /0.9999 /0.0003
sym2	0.0603 /0.9622 /0.0793	0.0347 /0.9871 /0.0263	0.0193 /0.9960 /0.0081	0.0113 /0.9986 /0.0028	0.0067 /0.9995 /0.0010	0.0046 /0.9998 /0.0005
sym4	0.0510 /0.9725 /0.0568	0.0263 /0.9917 /0.0170	0.0161 /0.9972 /0.0056	0.0096 /0.9990 /0.0020	0.0057 /0.9996 /0.0007	0.0039 /0.9998 /0.0003
sym6	0.0552 /0.9679 /0.0665	0.0303 /0.9902 /0.0200	0.0181 /0.9965 /0.0071	0.0103 /0.9988 /0.0023	0.0067 /0.9995 /0.0010	0.0044 /0.9998 /0.0004
cdf1.1	0.0478 /0.9757 /0.0499	0.0272 /0.9921 /0.0161	0.0162 /0.9971 /0.0058	0.0107 /0.9987 /0.0025	0.0076 /0.9994 /0.0013	0.0064 /0.9995 /0.0009
cdf3.1	0.0660 /0.9552 /0.0950	0.0369 /0.9855 /0.0297	0.0206 /0.9954 /0.0092	0.0119 /0.9984 /0.0031	0.0072 /0.9994 /0.0011	0.0048 /0.9998 /0.0005
cdf5.1	0.3991 /0.4717 /3.4772	0.2230 /0.6936 /1.0853	0.1251 /0.8636 /0.3414	0.0689 /0.9521 /0.1035	0.0423 /0.9810 /0.0391	0.0237 /0.9939 /0.0123

3. Results

3.1 Performance of adaptive denoising using lifting wavelet

Figure 4 shows the performance of adaptive denoising using lifting wavelet applied on a series of pulse signal. As shown in figure 4, the noise was successfully removed from the pulse wave signal.

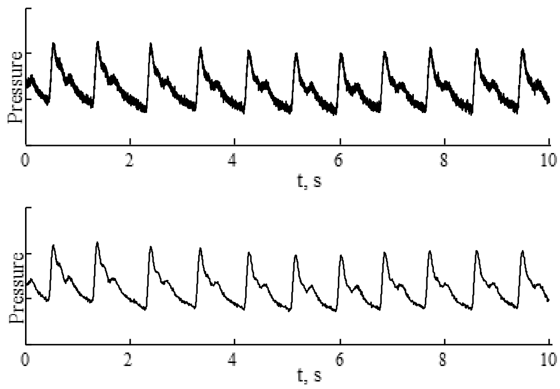

Figure 4. Performance of lifting wavelet denoising applied on a series of pulse.

3.2 Comparative analysis of lifting scheme and typical wavelet

Table 3 is the comparison among the denoising performance of applying typical wavelet denoising, adaptive denoising using typical wavelet and adaptive denoising using lifting scheme on pulse signal with different *SNR*. Each evaluation criterion were calculated by averaging all the criteria of the 15 data sets. Adaptive deonising using typical wavelet was implemented by adaptively select the wavelet basis using equations (5-6).

Adaptive denoising using typical wavelet showed best performance, with *MSE* and *SDR* larger and ρ smaller. With the increase of *SNR*, the difference between the adaptive denoising using lifting scheme and adaptive denoising using typical wavelet got smaller.

Table 3. Comparison among the denoising performance of applying typical wavelet denoising, adaptive denoising using typical wavelet and adaptive denoising using lifting scheme on pulse signal with different *SNR*.

SNR(*db*)	MSE_1[b]	MSE_2	MSE_3	ρ_1	ρ_2	ρ_3	SDR_1	SDR_2	SDR_3
5	0.0469	0.0438	0.1275	0.9766	0.9795	0.9269	0.0480	0.0419	0.2082
10	0.0256	0.0243	0.0695	0.9930	0.9936	0.9670	0.0143	0.0129	0.0654
15	0.0147	0.0138	0.0374	0.9977	0.9979	0.9806	0.0047	0.0042	0.0418
20	0.0088	0.0084	0.0251	0.9991	0.9992	0.9883	0.0017	0.0015	0.0283
25	0.0051	0.0049	0.0126	0.9997	0.9997	0.9988	0.0005	0.0005	0.0027
30	0.0035	0.0036	0.0084	0.9999	0.9999	0.9995	0.0002	0.0002	0.0025

[b]1represents denoising using typical wavelet; 2represents adaptive denoising using typical wavelet; 3 represents adaptive denoising using lifting scheme and LMS.

4. Discussion and Conclusion

This study applied the adaptive denoising using lifting wavelet on three kinds of pulse wavesingals. The adaptive denoising using lifting wavelet can effectively eliminate the noise of the pulse wave. The adaptive denoising using lifting wavelet showed comparatively poorer performance compared with the typical wavelet denoising and adaptive denoising using typical wavelet (*MSE*, 0.0469, 0.0438 and 0.1275, respectively, with *SNR* of the raw pulse signal 5db). As the *SNR* of the pulse signal increased, this difference between the performance of the adaptive denoising using lifting wavelet and the typical wavelet denoising and adaptive denoising using typical wavelet became smaller (*MSE*, 0.0035, 0.0036 and 0.0084, respectively, with *SNR* of the raw pulse signal 30db). However, this reduction in the performance of denoising, is a small price to pay to speed up the wavelet denoising and apply its application range.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Nos. 61374015 and 61202258), and the Fundamental Research Funds for the Central Universities (Nos. N130404016 and N110219001).

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