New Methods and Algorithms for Analyzing Human Physiological Signals of Long-Termed Heartbeat Rates

Tansheng Li, Yoshitsugu Yasui, Qian Tian, Noriyoshi Yamauchi

***Abstract*—**This research is about some new methods and algorithms for analyzing long-term heart beat rating data. To consider some characteristics of heart beat ratings, we compared several methods such as smoothing algorithm, wavelet-analysis with error elimination, application of low-pass filter and average method. All these methods and algorithms have their own advantages. Depending on different requirements, selection of different methods is available. When processing physiological signals, proper processing methods should be chosen.

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***Keywords*—**Heartbeat rate, Low-pass filter, Physiological signal processing, Wavelet analysis

I. Introduction

IN daily life, human health becomes more and more important. The WHO estimated that in 2002, 12.6 percent of deaths in the world were from ischemic heart disease. [1] Ischemic heart disease is the leading cause of death in developed countries, but third to AIDS and lower respiratory infections in developing countries.

As an example, Acute myocardial infarction results in a rapid heart rates that prevent the heart from pumping blood effectively. Cardiac output and blood pressure may fall to dangerous levels, which is the main reason to kill people [2].

In that condition, heart-beat rate can reach an impossible level, when it becomes faster than 200 times per minute, even 400 times per minute. If we can read this condition quick, more lives will be saved.

In a word, that means abnormal heartbeat rate is a very important mirror to MI. So direct monitoring of heartbeat rate is an effective method to watch over the risk of Myocardial Infarction.

In our own measurement, noise can make the sensor's heartbeat recording rate at 200/minute. For warning human health conditions, extract waves to monitor health conditions, and get rid of noises to avoid wrong warnings, data processing, for example de-noising, is the most important thing in this paper.

We choose the hardware of Polar Heart Rate Monitor S720i, and the software environment of Matlab R2008a.

Here is a figure of 24 hours' heartbeat. In this figure, every spots stand for the heartbeat pulses in the last minute. Data were taken every 15 seconds, which means every two neighbor spots have 15 seconds' interval. Zero point means no data.

In this figure, we can see there are much noise (pulse noise and so on) in data collecting. That is because in daily measurement, there can be many constraints, even obstructions against measurement. Due to our instruments, even changes of outer environments can affect the measurement, too. Besides, there are some periods of data error at the end of measurement.

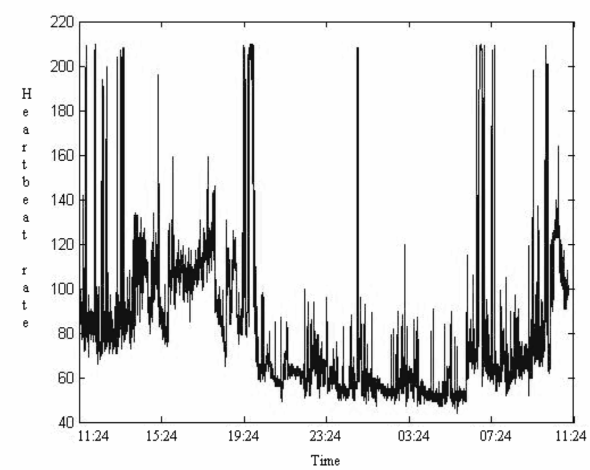

Fig.1 raw data of heartbeat rate in one day

Our research goal is to reduce or eliminate noises and errors, then extract the daily circle of human heart beat period in a day, and get algorithm for further realization.

II. Smoothing Algorithm

At first, we found the noises are very sharp. If we want to smooth the curve, we must deal with these peaks.

For sampling rate is 15 seconds, we can suppose that

Manuscript received May 31, 2008; Revised version received August 12, 2008. This work was supported in part by NTT Docomo.

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heartbeat rate cannot change over a value during 2 data. That means, for example,

The difference between data2 and data3, is the difference of heartbeat rate between 00:15-00:30 and 01:00-01:15. The average human heart is beating at 72 BPM [3]. Thus, the average heartbeat in 15 seconds is about 72/4=18 times, and in this smoothing algorithm, if difference between 2 data is over

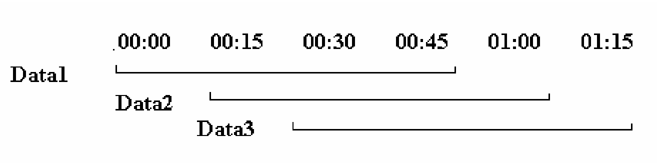


Fig.2 component of several heartbeat rate data

30, then in some 15 seconds, heartbeat rate may reach about 18+30=48 times. So we consider that as a noise.

In order to reduce peaks, the first assumption is that if we can average the two neighbor elements of each spot. So we use the algorithm below:

d (i)=(data(i-1)+data(i+1))/2;

Which means that we instead the current element with the average of its two neighbor elements. One advantage of this algorithm is it can be very easily realized in hardware design, because it is very easy to be written to gate circuits. But the biggest advantage is this algorithm can be used as recursive programs. Here's an example of Matlab program:

```
for j=1:100,
  for i=2:5931,
     d(i)=(data(i-1)+data(i+1))/2;
  end;
end.
```

And the result of using Smooth Algorithm is shown below.

From these figures, it is obviously shown that all the noises are smoothed into higher or lower values.

The disadvantage of this algorithm is that it has some distortion. In this condition of raw data, peak values should be cut as pulse noises, but that algorithm has smoothed that pulses

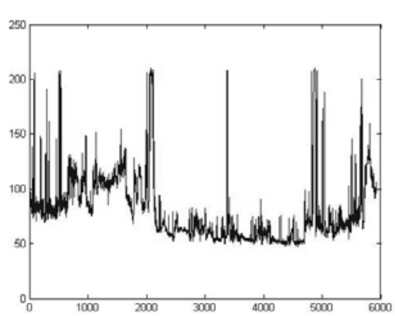


Fig.3 The algorithm is used once to process the raw data.

to other neighbor elements. That makes the measured average

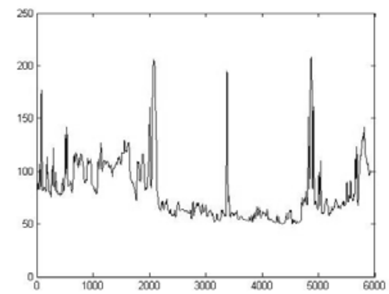
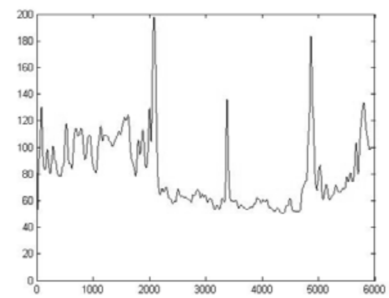


Fig.4 The algorithm is used 16 times to process the raw data.



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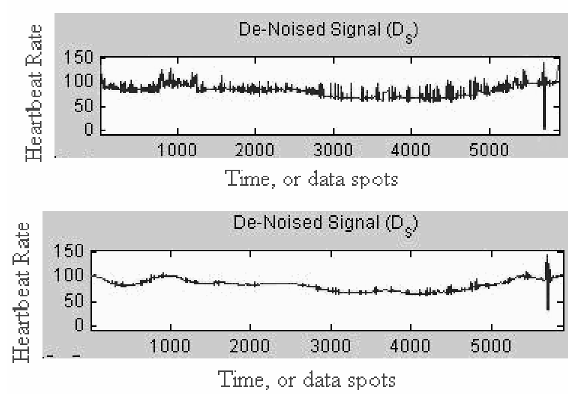

Fig.10 Db10, 8 levels of Daubechies wavelets de-noising from another raw data

heartbeat rate some kind of bigger than actual heartbeat rate. So we must find another choice.

III. Wavelet Analysis

Every multiplex-composed signal can be decomposed into several simpler signals, such as Figure 7.

In signal de-noising, we often use The Daubechies wavelets. The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support [4].

While we reduce noises, we use a threshold to compare with wavelets. The selection of threshold has two ways: hard-threshold and soft-threshold. Soft threshold is to compare the absolute value of current signal with the threshold. If the signal's absolute value is less than threshold, then let it be zero. If the signal's absolute value is larger than the threshold, then

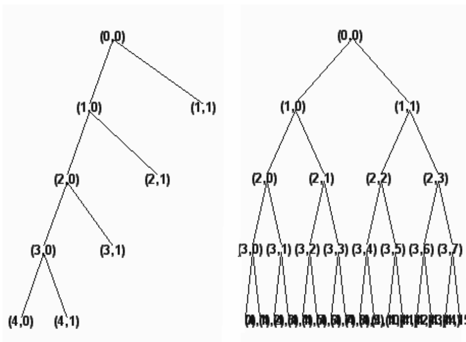

Fig.7 Method of complex signal de-composing

we replace it with the discrepancy between the absolute value and the threshold. For hard threshold, the difference to soft-threshold is that if the signal's absolute value is larger than the threshold, then keep it [5][6].

$$\hat{\omega}_{j,k} = \begin{cases} \omega_{j,k}, \left|\omega_{j,k}\right| \geq \lambda \\ 0, \left|\omega_{j,k}\right| < \lambda \end{cases} \text{ Hard-Thresholds}$$

$$\hat{\omega}_{j,k} = \begin{cases} \operatorname{sgn}(\omega_{j,k})(\left|\omega_{j,k}\right| - \lambda), \left|\omega_{j,k}\right| \geq \lambda \\ 0, \left|\omega_{j,k}\right| < \lambda \end{cases} \text{ Soft-Thresholds}$$

Using different parameters, we achieved some different results via Daubechies wavelets. Horizontal axis stands for time plot, vertical axis stands for heartbeat in one minute. The upper one is using hard-thresholds, the lower one is using soft-thresholds.

From the experiment results, we can see that the most efficient parameter is the level of Daubechies wavelets. And if we choose db10, 8 levels of Daubechies wavelets, we can get a good cycle of human heartbeat activities, except some obvious error. In another 24 hours' heartbeat data of Figure 9, the error is more classical. After processing by Daubechies wavelets, the obvious error still remains.

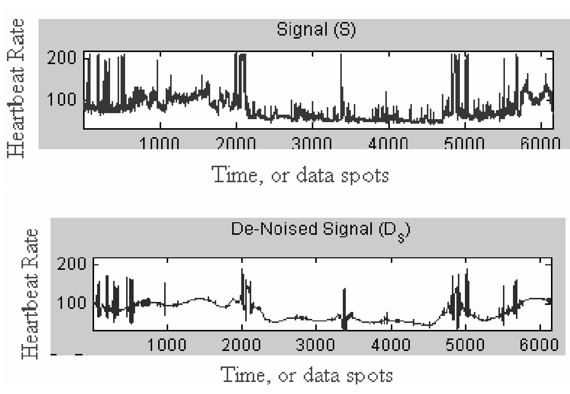

Fig.8 Db10, 8 levels of Daubechies wavelets de-noising from raw data

Figure 10 shows the different results via Daubechies wavelets. Horizontal axis stands for time plot, vertical axis stands for heartbeat in one minute. The upper one is using hard-thresholds, the lower one is using soft-thresholds.

Using different parameters, we can get different results via Daubechies wavelets. Figure 11 and Figure 12 shows these different results. But in all these figures, if the signal changes fiercely, there may be a peak value or a zero-value error. These

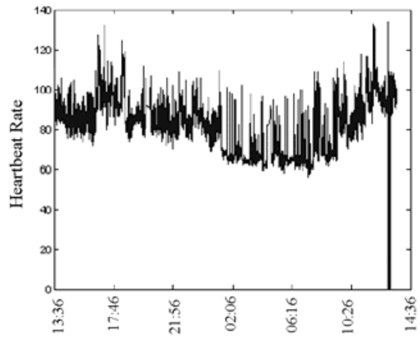

Fig.9 another raw data of heartbeat rate in one day

errors cannot be removed by wavelet analysis. So the method to remove these obvious error values became important.

IV. Error Elimination

Since every spots stand for the heartbeat pulses in the last minute, "Zero" value or "overflow" value are obvious errors. That is mostly taken by the detaching of sensor, or some other sensors besides, or some electronic obstructions

According to human biological knowledge, normal heartbeat rate is about 72 pulses per minute. And it cannot be changed very fiercely. For example, in this condition, heartbeat rate can have a change of 60 in 15 seconds. So for reducing errors, we've got another method:

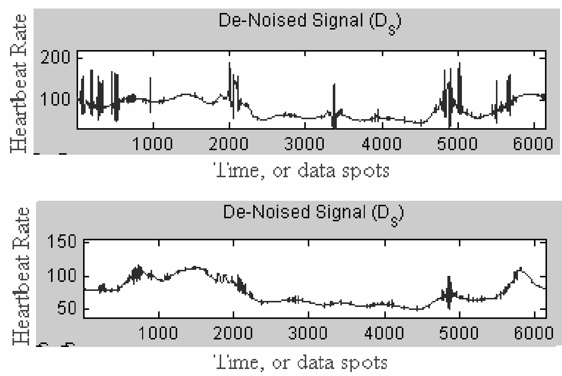

Fig.14 comparison of wavelet transforming results

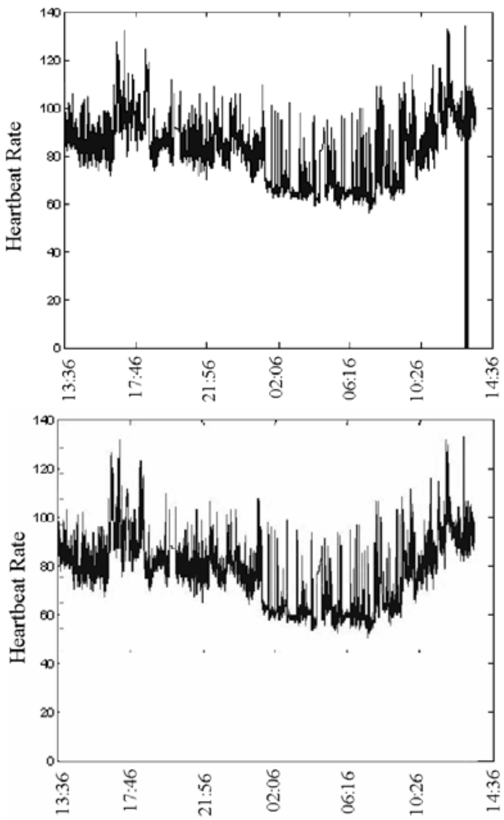

Fig.15 the other raw data and result after error elimination

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that it can be done recursively. In figure 13, plot (2) still has two long-period errors. But while we apply this method for a few times, all the errors disappeared.

The error elimination algorithm is very effective on wavelet transform, especially Daubechies wavelet. The figure 14 shows the compare of wavelet transform results. The upper one is raw data processed with Daubechies wavelet. The lower one is raw data processed with error elimination algorithm 4 times, then be processed by Daubechies wavelet.

For proving the ability of error elimination algorithm, the other raw data is also processed by this method. The compare of

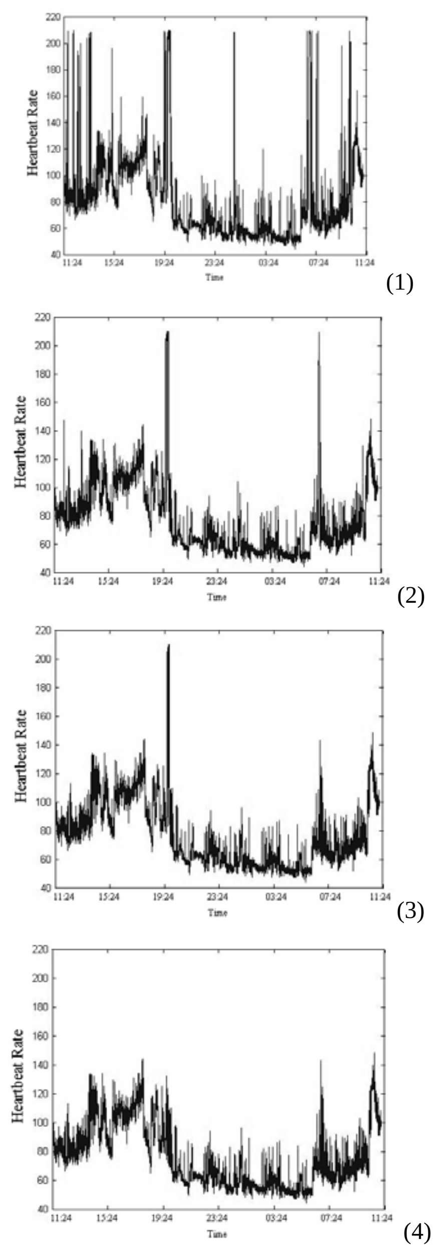

Fig.13 effect of error elimination algorithm

results are shown below. Figure 15 compares the other raw data and result after error elimination, figure 16 shows the result of Daubechies wavelet from two plots of figure 15.

V. Interval and Energy Methods

A. Interval Methods

In signal processing, sampling is the reduction of a continuous signal to a discrete signal. A common example is the conversion of a sound wave (a continuous-time signal) to a sequence of samples (a discrete-time signal). If we don't require much accuracy, we can surely use interval methods to simplified computation. That is useful in hardware design.

For Interval 16, the algorithm is very simple:

D(i)=data(16*i);

That means we take one data every other 16 raw data. For this sampling, raw data became as figure 17.

After extending the data, we used the same procedure to process this data in wavelet analysis. Then we got a failure figure.

In this figure, although “Zero Value Error” is lost during sampling, in this condition, signal became unrecognizable. Considering the importance and result of choosing different parameters in wavelet analysis, some other low-accuracy parameters are chosen to get better waveform. This figure shows the comparison of wavelet transform using different parameters. From this comparison, we can see the importance of parameter choosing in wavelet analysis. The upper plot is the failure result, the lower plot is the result of db10, 4 levels of Daubechies wavelets de-noising after processing by interval 16.

We can find that “Zero Value” is lost during sampling. And this result displayed a much better result than before.

B Energy Method

All the human activities provide energy. Especially, human heartbeat energy is responded by heartbeat rating: if heart beats faster, more energy is created; if heart beats slower, then less energy is created.

If the average energy curve can be measured, the waveform must be smoother. Because Energy equals to Power multiplies Time, energy changing with time becomes more illustrative. So that we consider average heartbeat as a view of energy, an algorithm occurs to solve this waveform:

```
for i=1:360
{
for j=0:16
     g(i)=g(i)+(d(i+j));
   g(i)=g(i)/16;
  }
```

Figure 19 shows the data from procedure of energy method, comparing with the raw data; figure 20 shows the wavelet analysis result after processing by energy method, comparing with the result from interval method. The parameter of wavelet analysis is db10, 4 levels of Daubechies wavelets de-noising, soft-threshold is used.

Comparing with Interval signals, in the same de-noising condition, energy algorithm can reduce more noises, but the waveform is a little different from Interval algorithm. That’s because the energy algorithm is the average of every 16 data, and the interval algorithm is a simple sampling. Although the energy algorithm has some distortion, it considers noise as normal data. But it is still better than interval algorithm in de-composing. Noise in energy algorithm is smoothed by its neighbor data, but it cannot be smoothed in the interval algorithm, because the interval algorithm is only sampling.

VI. Application of Low-pass Filter

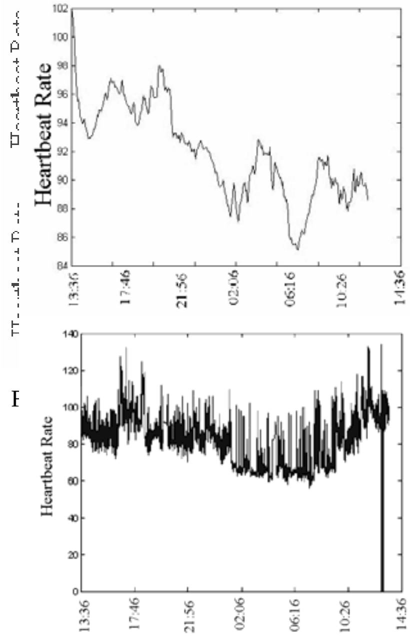

Fig.19 result of energy method, comparing with raw data.

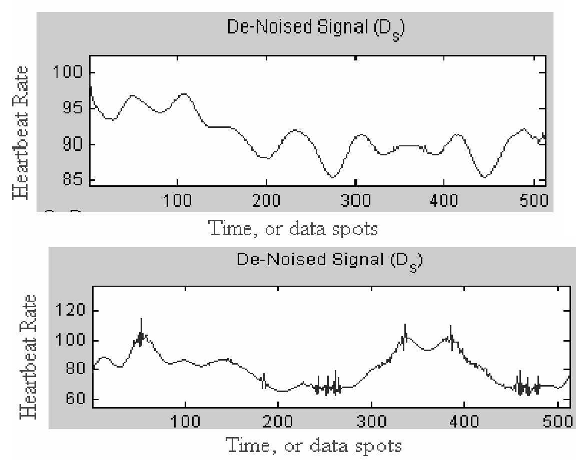

Fig.20 result of wavelet analysis after processing with energy method, comparing with result after processing with interval method

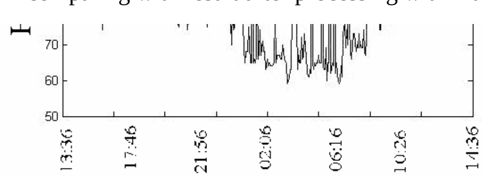

Fig.17 raw data and Interval/Sampling result

Look back to the raw data, the signal looks like a low-frequency signal, with many pulse noises. In electricity signals processing, we often use a filter to adjust the waveform.

Digital filters can have two classifications: Infinite impulse response (IIR type) or Finite impulse response (FIR type). While realizing same design specifications, IIR has lower levels than FIR. But in realization, for same levels of these two kinds of filters, IIR type has to do more multiply calculations than FIR type. On the other hand, FIR type can be designed as liner filter easily. Basically, IIR type has less computation complexity than FIR type.

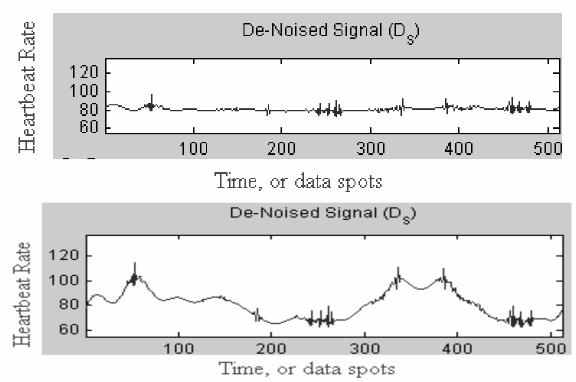

Fig.18 comparison of the two results of Daubechies wavelet with different parameters after interval 16 processing

The raw data can be written as:

$$y[n] = b_0 x[n] + b_1 x[n-1] + \dots + b_N x[n-N]$$

Where x[n] is the input signal, y[n] is the output signal and bi are the filter coefficients. N is known as the filter order; an Nth-order filter has (N + 1) terms on the right-hand side; these are commonly referred to as taps.

The previous equation can also be expressed as a convolution of filter coefficients and the input signal:

$$y[n] = \sum_{i=0}^{N} b_i x[n-i]$$

To find the impulse response ,we set

$$x[n] = \delta[n]$$

where delta[n] is the Kronecker delta impulse. The impulse response for an FIR filter is the set of coefficients b(n), as follows

$$\begin{aligned} h[n] &= \sum_{i=0}^{N} b_i \delta[n-i] \\ &= b_n \end{aligned}$$

For n=0 to N

The Z-transform of the impulse response yields the transfer function of the FIR filter [7].

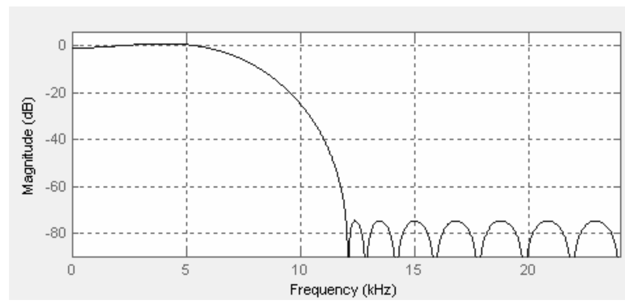

Fig.21 magnitude response plot of the FIR filter above

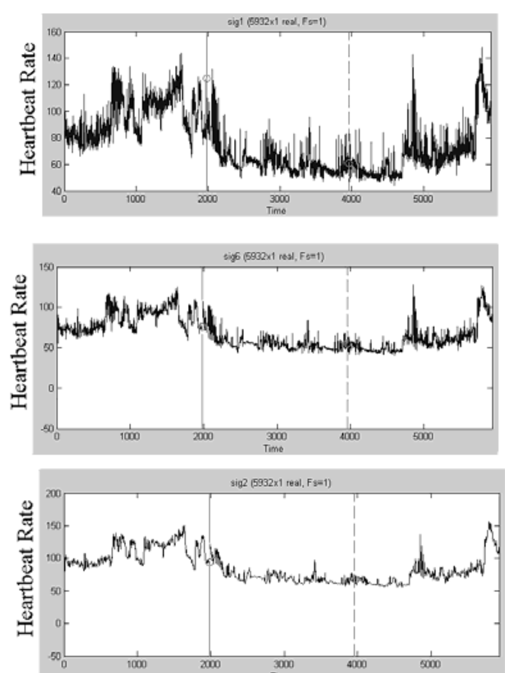

Fig.22 result of using FIR filter to process raw data.

$$H(z) = Z\{h[n]\} = \sum_{n=-\infty}^{\infty} h[n] z^{-n} = \sum_{n=0}^{N} b_n z^{-n}$$

In this research, we choose FIR filter. The design specification is shown below:

Response Type:	Low-pass FIR Equiripple Filter
FS(sampling rate):	48000
Frequency Pass:	6000Hz
Frequency Stop:	12000Hz

Figure 21 shows the magnitude response plot.

We choose the original raw data without peak value error as the first plot. And as the second plot, most of the peak noises are eliminated by this filter. The next plot shows another filter with different parameters of:

FS(sampling rate):	3000
Frequency Pass:	140Hz
Frequency Stop:	600Hz

And for processing the other raw data, which has the zero-value data to check the ability of FIR filter, Figure 23 shows the result. In the result comparing with raw data, we can see that the FIR filter cannot eliminate peak value or zero value error very well.

VII. Conclusion

While measuring or transferring human physiological information, signals become very noisy. Comparing with methods mentioned above, for basic recognizing and direct viewing of human heartbeat rate in one day, smoothing algorithm is better because of its simple format. For analyzing human daily cycle with more accuracy, wavelet analysis with error elimination comes better. It reduces nearly all the noises and sharp values into a smooth curve. For analyzing human short-period activities in several minutes of a day, data via Low-pass filter is the best choice. At last, because plot using interval or average method has the best balance between de-noising and data distortion, it is the best way to analyze human daily cycles. Anyhow, Error elimination doesn't affect normal signals at all, and it can reduce obvious signals very well, so apply of error elimination algorithm is strongly recommended before any other signal processing.

Acknowledgment

Tansheng Li thanks his supervisor and Professor Takaaki BABA and Professor Tsutomu YOSHIHARA for their insightful comments, excellent advice and patience throughout the progress of this research and the toughest time in his study. He also thanks NTT Docomo cooperators and his laboratory members for their valuable information, penetrating insight and kind encouragement.

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