The Multi-parameter Physiologic Signal Reconstruction by means of Wavelet Singularity Detection and Signal Correlation

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Abstract

A novel approach for reconstructing lost data from correlative signals among multi-parameter physiologic signals is proposed in this paper. The approach extracts a sample form a target signal that has data lost, and then lays the sample one by one according to singularity of a reference signal that has tight correlation with the target signal, to form a reconstructed signal in which a substitution of lost data is included. Our experiments confirm that this approach is effective for reconstructing signal having typical waveform sample and random time interval variations, especially for the data reconstruction application that requires real time processing.

1. Introduction

Reconstructing corrupted or lost data from multi-parameter physiologic signals becomes essential for a real-world monitoring application. There are some approaches available for data reconstruction and among those one of the most commonly used is Neural Networks (NN) [1][2]. NN approach can estimate a signal with good precision in time and in amplitude, by learning from history data that may be a time consuming processing, thus is difficult to be employed at applications that require real time processing.

Considering that in some case, providing a basis for reliable estimation of the timing of major fluctuations in a signal (such as QRS complexes in an ECG signal) can be significant, we propose a real-time algorithm that can reconstruct the lost data among a group of correlative signals with high timing precision.

2. Method

2.1. Wavelet singularity analysis

Wavelet Transform is employed in proposed approach for signal singularity analysis [3]. A wavelet is a function $\psi \in L^2(R)$ with a zero average:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \quad (1)$$

It is normalized $\|\psi\| = 1$, and centred in the neighbourhood of $t = 0$. Scaling ψ by s and translating ψ by u, a set of time-scale bases are obtained:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-u}{s})$$

These bases remain normalized: $\|\psi_{u,s}\| = 1$.

The Continuous Wavelet Transform (CWT) of $f \in L^2(R)$ at the time u and scale s is

$$Wf(u,s) = \int_{-\infty}^{=\infty} f(t)\frac{1}{\sqrt{s}}\psi^*(\frac{t-u}{s})dt \quad (2)$$

One of important properties of Wavelet transform is its ability of detecting signal singularity: the wavelet-transform-coefficient $Wf(u,s)$ changes in proportion to signal dv/dt. In other words, the wavelet transform can detect signal rise and fall sides that bear high dv/dt value, thus can be used to detect accurately the signal time events.

2.2. Signal correlations

In order to evaluate the timing accordance of lost data and reconstructed data, the cross-correlation function is applied [4]. The cross-correlation function for two signals is given by:

$$R_{xy}(m) = E\{x_{n+m}y_n^*\} = E\{x_n y_{n-m}^*\} \quad (3)$$

Where xn and yn are jointly stationary random signals and E{} is the expected value operator. If the signals xn and yn are uncorrelated, the cross-correlation function will be zero. If the two signals are correlated, it will reach its maximal value when m corresponds to the time lag between the two signals. In practice, only finite segment of signals are available. The raw value of cross correlation function is calculated by

$$\hat{R}_{xy}(m) = \begin{cases} \sum_{x=0}^{N-m-1} x_{n+m} y_n^* & m \geq 0 \\ \hat{R}_{yx}^*(-m) & m < 0 \end{cases} \tag{4}$$

2.3. Reconstruct data by means of Wavelet Singularity Detection and Signal Correlation.

Physiologic signal is pseudo-periodic signal in which the period fluctuates randomly. Because the period variation is random, it is difficult to precisely predict the periods of reconstructed data. On the other hand, multi-parameter physiologic signals are usually strongly corrected each other and such that correlations are constant, that make up the possibility of reconstructing the lost data in high timing precise from correlative signals in which the period fluctuates in the same random way as in lost data.

The proposed approach is based on below phoneme: some physiologic signals, such as CEG, consist of mainly a series identical basic waveform (sample) in different time interval (period). Our methodology is to construct a sample from the target signal (the signal has data lost and need to be reconstructed), then lay the sample one by one at different time interval according to the singularity of the signal that correlates to the target signal, to form a reconstructed signal, a substitution of the target signal, and the final 30 second data at reconstructed signal can be a substitution of lost data. Below we illustrate the data reconstruction process by going through an example.

3. Example of application

The data a39 giving for CinC 2010 competition is used as the signal under study. The a39 physiologic data consists of six signals as illustrated in Figure 1, and one indicated in bottom frame of the Figure 1 is the target signal (ABP signal) that lasts ten minutes and has final 30-second data lost (not illustrated in Figure 1), our task is to reconstruct the lost data.

Step 1: construct a sample. The sample is extracted from the target signal and illustrated in top frame of Figure 3. It covers a time interval (about 102 point's data) that equals the average period of the target signal, and can be extended at right end to overlap the bigger interval according to correlative signal (reference signal).

Step 2: Chose reference signal. Besides the target signal, all other signals are calculated cross correlation with target signal according to equation (4) and the one has the highest correlation value with the target signal is chosen as a reference. In this example, 3th signal (ECG signal) from top to bottom at Figure 1 has been chosen as a reference signal.

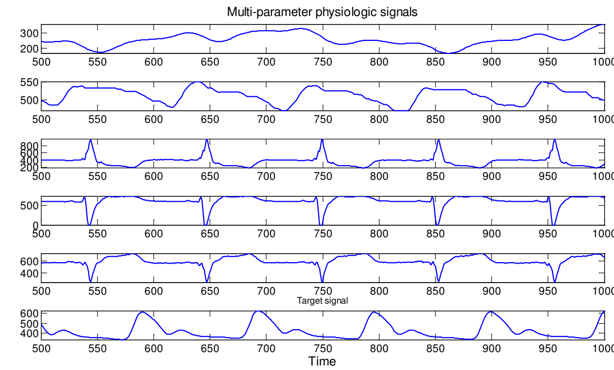

Figure 1. Multi-parameter Physiologic Signal.

Step 3: Calculate signal singularity. Wavelet transforms at target signal and reference signal are carried out according to equation (2). To simplify the calculation, s in equation (2) is set to 1, resulting at $Wf(u,s)$ coefficient curves illustrated by dotted line and marked "singularity" in legend box in Figure 2. The peaks of singularity curve are further detected and illustrated in Figure 2 and marked "singularity peak" in legend box.

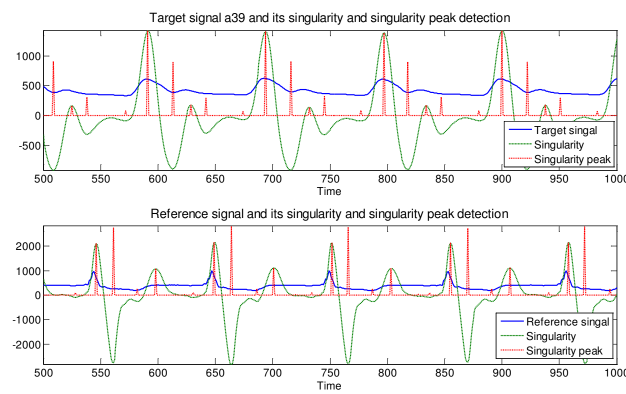

Figure 2. Signal and its singularity and singularity peaks.

Step 4: Lay sample according to reference signal singularity peaks. The samples are laid according to and aligned with the singularity peaks of the reference signal, forming a reconstructed signal, as illustrated in Figure 3. There may be multi peaks available as references for aligning samples but with average period of the target signal, it is easy to select one that is nearest to the average period interval as a reference. Also the amplitude of peaks can be a ruler for identifying right references. The reconstructed signal is at least one period longer than the target signal, and is calculated correlation with target signal according to equation (4). The correlation calculation results will reach its maximal value when m in equation (4) corresponds to the time lag between reconstructed and target signals. Shift m points of reconstructed signal to align with target signal, and extract first 10 minutes data from reconstructed signal as a final reconstructed signal. The last 30 second data of the final reconstructed signal will be a substitution of the lost data in target signal. A comparison of lost data and reconstructed data is illustrated in Figure 4.

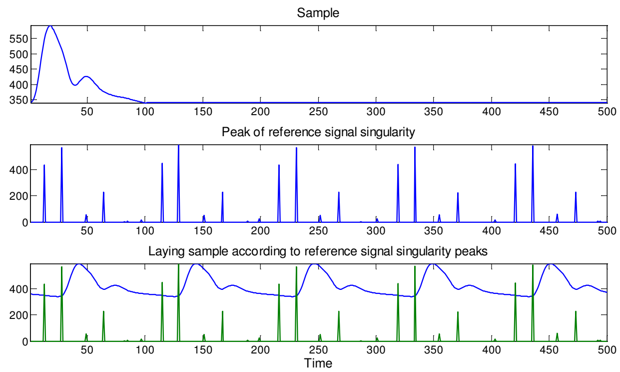

Figure 3. Lay and align sample according to reference singularity.

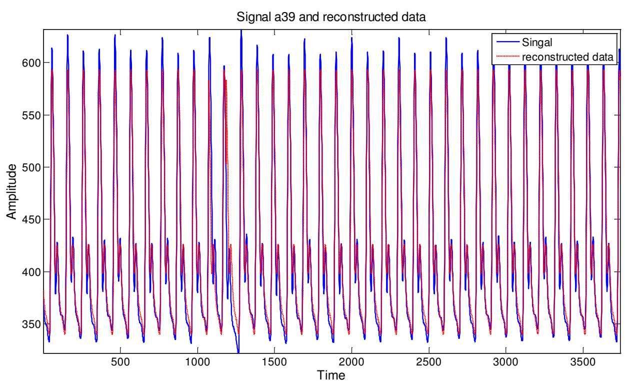

Figure 4. Comparison of lost data and reconstructed data.

4. Experimental results

We have treated 100 signals in datasets C with both singularity detection approach and NN approach to reconstruct lost data, and adopt the results with higher amplitude and timing accordance scores. The approach gives higher amplitude accordance score plus timing accordance score is elected for each signal and the elected times under different signal type for each approach are recorded and illustrated in Table 1, indicating that for the signal type PLETH, ABP, RESP and ART, the singularity detection approach is more effective.

5. Conclusion

A novel approach for reconstructing lost data from correlative signals among multi-parameter physiologic signals is proposed in this paper. The approach extracts a sample form a target signal that has data lost, and then lays the sample one by one according to singularity of a reference signal that has tight correlation with the target signal, to form a reconstructed signal in which a substitution of lost data is included. Our experiments confirm that this approach is effective for reconstructing signal having typical waveform sample and random time interval variations and can reach above 95% accuracy in timing, and is more effective than NN approach when treat with signals of PLETH, ABP, RESP and ART, and is advantaged at real time processing. For the signals that have no strong correlation signal available or are sensitive to amplitude variation, NN approach is adopted. We used both approaches to calculate signals in datasets A, B and C used by CinC 2010 competition, and adopt the results with higher scores. The singularity approach is adopted by 49%, 42% and 49% signals in datasets A, B and C respectively, and the final scores in datasets C are 63.59 and 77.36 for event 1 (amplitude sensitive) and event 2(timing sensitive) respectively.

Table 1. Singularity detection approach and Neural Networks approach elected number under different signal types in datasets C

	ECG	**PLETH**	**ABP**	**RESP**	**CVP**	**ART**
Sing.	**9**	**8**	**13**	**10**	**3**	**3**
NN	34	5	4	2	4	0
Total	**43**	**13**	**17**	**12**	**7**	**3**

- The data with zero score are not included

References

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[4] Matlab help file in xcorr() function and dden cmp function, www.mathwork.com .

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