Reconstructing Missing Signals in Multi-Parameter Physiologic Data by Mining the Aligned Contextual Information

Yanen Li[1], Yu Sun[2], Parikshit Sondhi[1], Lui Sha[1], Chengxiang Zhai[1]

[1]Department of Computer Science, University of Illinois, Urbana, Illinois, USA
[2]Department of Mechanical Science and Engineering, University of Illinois, Urbana, Illinois, USA

Abstract

The PhysioNet Challenge 2010 is to recover missing segments of a particular signal in the given multi-parameter physiologic data set. In this paper we propose a contextual information based framework to achieve robust reconstruction. For a given target signal that is to be reconstructed, our algorithm intelligently choose among three sub-algorithms to best recover the missing segments. Experiments are carried out on the Physionet/ CinC Challenge 2010 data sets. The results show that the proposed method is particularly effective on signals that have well aligned contextual signals.

1. Introduction

Real-time monitoring of physiologic signals is an important clinical tool for intensive care of patients. However, transient corruption or loss of one or more signals could prevent accurate interpretation of the signals and mislead the downstream analysis. Therefore robust reconstruction of physiologic signals can be very useful in real-world monitoring scenario. The reconstructed signal should be consistent not only with respect to its previous history but also with respect to its relationships with other signals. This calls for an approach that can explore both the structure of the signal itself and its dependency on several other physiologic signals. Due to the rich structure and high complexity of the problem, robust reconstruction of physiologic signals utilizing multi-parameter information remains a research challenge.

The reconstruction of one physiologic signal from itself, or several other signals, has been studied extensively in literature, see [1–6]. Various techniques are available, depending on the different properties of the target signal S_t, and the reference signal S_r: wavelet transformation [3], adaptive filtering [4], just to name a few.

In the PhysioNet Challenge 2010, the target signal can be any of the given physiologic signals (BP, RESP, ECG, PLETH, etc). The task of recovering different signals may differ a lot in nature. Therefore, a good solution should be able to adaptively choose an algorithm based on available information so as to deliver the best performance. In this paper our proposed reconstruction algorithm consists of three main functional components: linear regression based prediction, contextual information based pattern-matching, and the ECG-derived respiration reconstruction. For a given target signal that is to be reconstructed, our algorithm intelligently choose among these three sub-algorithms to best recover the missing segments.

The rest part of this paper is organized as follows: Section 2 gives the problem formulation; Our approach is presented in Section 3; Experiments and results are discussed in Section 4; Section 5 concludes our algorithms and results with discussion of possible improvements.

2. Problem statement

The aim of PhysioNet Challenge 2010 is to develop robust methods for filling in gaps in multi-parameter physiologic signal (including ECG signals, CVP signal, ABP signal, respiration, etc.). These signals are generated from multi-parameter recordings of patients in intensive care units (ICUs). The gaps are signal segments intentionally removed from original signals, and need to be recovered 'using any combination of available prior and concurrent information'.

Figure 1 gives an example of multi-parameter physiologic signal and the missing segments. In the rest part of this paper, we refer to the signal with missing segments as target signal, denoted by $S_t(t)$, some times S_t for short. We call the signal(s) that the reconstruction is based on the 'reference signal(s)', denoted as $S_r(t)$ or S_t. The reconstructed signal is denoted as $S_{rec}(t)$ or S_{rec}.

3. Methods

We observe that the performance of the signal reconstruction strongly depends on the type of signals to be reconstructed. Instead of designing a single algorithm that is capable of addressing all these different situations under a

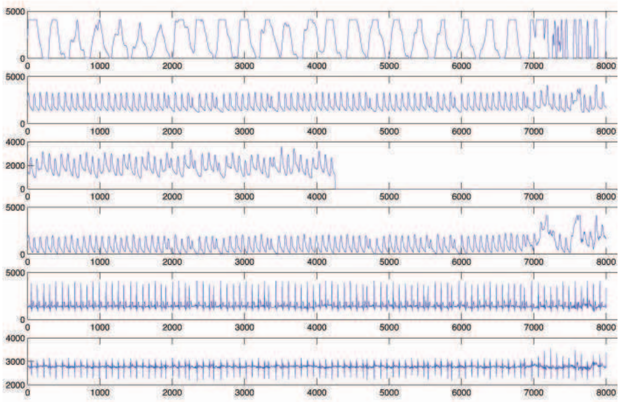

Figure 1. Typical Multi-parameter Physiologic Signals and the Gap

unified framework, we proposed a solution that is a combination of several different algorithms. Each of them is straightforward to implement, and is designed to recover a specific type of signals. Our algorithm first classifies the problems into 3 types according to the target signal. The problem belongs to 'Type I' if its target signal has strong correlation or cross correlation with another synchronized signal (the cut-off value is set to 0.7 in this work). 'Type II' signals represent target signals which have well aligned concurrent signals, and thus they fit into the model of Pattern Matching with contextual information. These signals include ABP, PLETH, CVP, etc. 'Type III' signals represent the respiration signals. The respiration signals are much more noisy than other signals, and have relatively poor synchronized signals.

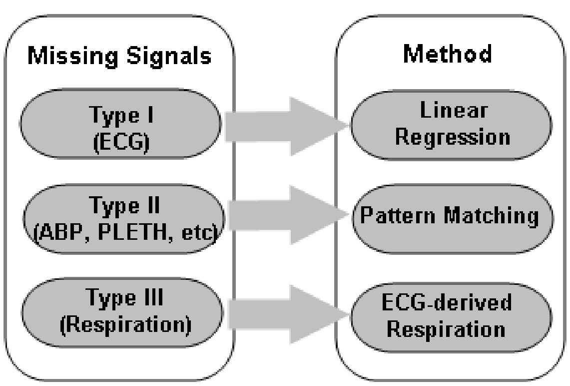

Figure 2. Schematic Plot of Signal Reconstruction Process

Different types of problems correspond to different reconstruction algorithms, as illustrated in Figure 2. In Type I problem, the missing signal is reconstructed using linear regression. Type II problem is solved by pattern matching. Type III problem is solved by the ECG-derived respiration algorithm. These reconstruction algorithms are elaborated in the following sections.

3.1. Reconstruction of type I signals by regression

This reconstruction method is based on the observation that there are strong correlation between Type I signal (such as ECG signals) and another reference signal (usually another ECG signal). Our experiments show that the correlation coefficient between the two signals can reach 0.95. So when moderate error in the reconstructed signal is tolerable, it is safe to assume linear relationship between target and reference signals.

$$S_t(t) = aS_r(t) + b + \epsilon \tag{1}$$

where t is the discrete time indices, a and b are scalar coefficients characterizing linear relation between two signals, ϵ is the noise or fitting error.

To obtain a and b, we take segments of history data from both target and reference signals. Denote the data vectors as $S_t(t_1 : t_W)$ and $S_r(t_1 : t_W)$, respectively. The length of signal segment W is adjustable according to desirable accuracy and computational resource available. Coefficients a and b can be readily estimated by linear regression.

Therefore if a segment of one Type I signal S_t is missing, it can be easily recovered from another signal S_r using *Eq.* (1). When there are multiple signals available as reference signals, our algorithm calculates their correlation with the target signal, identifies the one that has highest correlation coefficient with the target signal S_t, and then use it to reconstruct the missing target signal. The correlation coefficient is defined by:

$$corr_{S_t,S_r} \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} \frac{(S_t(\tau) - \bar{S}_t) \cdot (S_r(\tau) - \bar{S}_r)}{Std(S_t) \cdot Std(S_r)} d\tau \tag{2}$$

Where $\bar{S}_t$ and $\bar{S}_r$ are the means of S_t and S_r, $Std(S_t)$ and $Std(S_r)$ are standard deviation of S_t and S_r, respectively.

There are scenarios that the best correlated reference signal still has low correlation with the target signal, but the cross correlation between the two is high. This is usually due to the phrase shift between two signals. Therefore, in order to search for the reference signal with closest co-occuring relationship, we also calculate the cross correlation between the target signal S_t and any other reference signal S_r

$$cross\_corr_{S_t,S_r}(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} S_t(\tau)\, S_r(t+\tau)\, d\tau \tag{3}$$

And choose the one that has highest correlation or cross correlation:

$$\hat{r} = \arg\max_{r} \left(Max \begin{cases} corr(S_t, S_r) \\ cross\_corr(S_t, S_r) \end{cases} \right) \quad (4)$$

Once the reference signal is found, we fit the linear regression correlation coefficients and reconstruct the missing segment of target signal S_{rec} with these parameters. Note that some post-processing is needed if the best reference signal is found by using cross correlation; that is, align the target signal and the reference to compensate the phrase shift.

3.2. Reconstruction of type II signals by pattern matching

For Type II signals, we employ a pattern-matching reconstruction algorithm called PatMatch. The idea behind PatMatch is to use ECG signal for both time-reference and reconstruction.

Suppose that one ECG signal is chosen as reference S_r. Each segment of S_r between two consecutive R-waves is called a 'frame'. We then treat both signals S_r and S_t on a frame-by-frame basis. Let $i \in I := \{1, 2, \cdots\}$ be the indices of frames, and T_i be the discrete time indices corresponding to frame i, $i \in I$. We call a frame of reference signal $S_r(T_i)$ the 'contextual information' of $S_t(T_i)$, which is its corresponding frame in the target signal. The philosophy here is, the information that is needed to reconstruct $S_t(T_i)$ is provided in $S_r(T_i)$. To be more specific, we assume that whenever $S_r(T_i)$ repeat some previous pattern $S_r(T_j)$ for $j < i \in I$, then it is highly likely that $S_t(T_i)$ will be 'similar' to $S_t(T_j)$. Therefore, when $S_t(T_i)$ is not available, it is possible to recover it from $S_t(T_j)$. The reconstruction task now reduces to a 'pattern matching' carried out between frame $S_r(T_i)$ and all previous frames $S_r(T_n), 1 \leq n < i$. After the best match $S_r(T_j)$ is found, $S_t(T_i)$ can be reconstructed by simply 'cut and paste'. Please note that in the 'cut and paste' step, we need to fill in 0s if the length of T_i is bigger than T_j; on the other hand, we just ignore the tailing signals in $S_t(T_j)$ if the length of T_j is bigger than T_i.

Note that this assumption is by no means verified from physiological point of view. The relationship between two such physiologic signals is far more complex (think about the underlying mechanism that generates these signals). We make this assumption here because of the convenience it brings about: it leads to a simpler and robust algorithm which captures the information content that S_r carries about S_t. Reconstruction results in Section 4 shows reasonable performance for a wide range of signals.

A key component that affects performance much is the metric that we use to compare two frames. In this work, we use a weighted combination of correlation coefficients

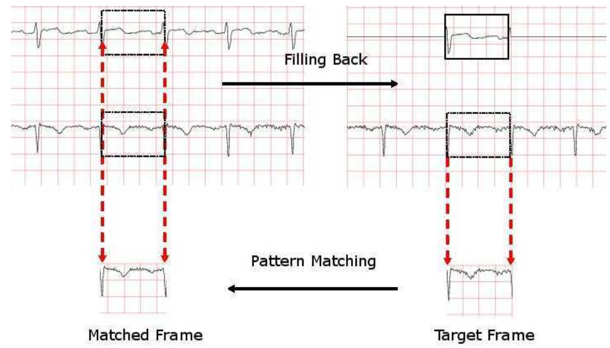

Figure 3. Illustration of the Pattern Matching Algorithm

and the square of Euclidean distance between two frames:

$$sim\left(S_r(T_i), S_r(T_j)\right) = \lambda \cdot [corr(S_r(T_i), S_r(T_j))] + (1-\lambda) \cdot \|S_r(T_i), S_r(T_j)\|^2 \quad (5)$$

The similarity measure $sim\left(S_r(T_i), S_r(T_j)\right)$ considers both the metrics in the Event 1 and Event 2 evaluation. The weight λ is learned by Powell Search in the training data sets A and B. Powell Search is an efficient and powerful search algorithm for finding the minimum/maximum of a un-derivable function with multiple parameters. Please refer to [7] for the Powell algorithm details. The optimal value of λ we obtain in the training sets is 0.562, slightly biased toward the correlation between two frames. The Pattern Matching algorithm details, including frame detection, closest frame identification, 'cut and paste' with 0 filling, are summarized in *Algorithm 1*.

3.3. Respiration signal reconstruction

The Type III signals, i.e. Respiration Signals, are particularly hard to reconstruct due to the intrinsic irregular patterns of that signal and the lack of well aligned contextual signals. We have tried the Pattern Matching algorithm but the result is very poor, indicating the Pattern Matching algorithm is not suitable for this type of signals. We instead employ the ECG-Derived Respiration idea for reconstructing a respiration signal [5]. It's based on the relation between the movement of ECG electrodes on the chest surface and the respiratory cycle. We first identify the peaks of an ECG signal and use the same algorithm described in [5] to derive the missing Respiration signals.

4. Experiments and results

The 2010 PhysioNet Challenge was to predict the last 30 seconds of a physiological waveform given 9 minutes and 30 seconds of its previous history and 10 minutes of N different concurrent physiological recordings (sampled

Algorithm 1 Pattern Matching

Require: target signal S_t,
reference ECG signal S_t, weight λ .
Ensure: reconstruction of missing segment S_{rec}

Initialize frames $S_r(T_i), i \in \{1, 2, \cdots\}$:
identify the R-R intervals in S_r, then
$S_r(T_i) := S_r([R_k : R_{k+1}]), k \in \{0, 1, \cdots\}$
for each time frame T_i in the missing segment
repeat
$T_{max} = \arg\max_j \{sim(S_r(T_j), S_r(T_i))\}$
if $|T_{max}| > |T_i|$ **then**
$S_{rec}(T_i[1, 2, \cdots, n]) := S_t(T_{max}[1, 2, \cdots, n])$,
where $T_i = T_i[1, 2, \cdots, n])$
else
$S_{rec}(T_i[1, 2, \cdots, n']) := S_t(T_{max}[1, 2, \cdots, n'])$,
$S_{rec}(T_i[n' + 1, n' + 2, \cdots, n]) := 0$,
where $T_{max} = T_{max}[1, 2, \cdots, n'])$,
$T_i = T_i[1, 2, \cdots, n])$
end if
until $T_i = T_{end}$
return S_{rec}

at 125 Hz). There are three datasets (set A, B and C) in total, each of which contains 100 series of records. The evaluation metric is the sum of quare errors (Event 1) and correlation (Event 2) between reconstructed signals and the ground-truth. Results on the three datasets show that our models effectively reconstruct the missing signals. We achieve the accumulative score of and 47.74 at event 1 and 65.48 at event 2 in the final evaluation Set C. Compared to Set C, we obtain better performance in Set A and B in both Events. The results in these datasets are listed in *Table 1*

Table 1. Reconstruction Results in Physionet Datasets

	Set A	Set B	Set C
Event 1	60.31	58.36	47.74
Event 2	76.90	73.52	65.48

5. Discussion and conclusion

There is a relatively big gap in performance between Set C and other two datasets. A careful look into the results reveals that the major reason why Set C is performed poorer is due to the bad performance of 15 Respiration signals. *Table 2* shows the average score in each type of the signals (average score is from 0 to 1). It indicates that the performance in Type I and Type II signals are satisfying. This also shows that our regression based algorithm and the PatMatch algorithm are very effective in reconstruction of Type I and Type II signals. The bad results on Type III signals suggest that the ECG-derived respiration method is not suitable for these datasets, or our implementation of that idea does not performs well.

Table 2. Reconstruction Results By Signal Type

	Type I	Type II	Type III
Number	35	51	14
Event 1	0.82	0.36	0.049
Event 2	0.92	0.60	0.21

In the pattern-matching algorithm, when we are comparing two slices of ECG signal, the similarity metric is the combination of correlation and square of Euclidean distance between those two slices. This may not be the best criterion for comparing two slices of signals. Some other metrics, which take the shape of the wave form into consideration, might be better for this problem.

To conclude, the aligned contextual information is crucial for missing signal reconstruction. Our regression model and PatMatch model effective unitilize the contextual information and successfully reconstruct the missing segments in Type I and Type II signals.

Acknowledgements

This paper is based upon work supported in part by the National Science Foundation under grant CNS-0834709.

References

[1] Mukhopadhyay S, Sircar P. Parametric modelling of ECG signal. Med. Biol. Eng. Comput. 1996 Mar;34(2):171-174.

[2] Khadra L, al-Fahoum AS, al-Nashash H. Detection of life-threatening cardiac arrhythmias using the wavelet transformation. Med Biol Eng Comput. 1997 Nov;35(6):626-632.

[3] Addison PS. Wavelet Transforms and the ECG: a review. Physiol Meas. 2005 Oct;26(5):155-199.

[4] Thakor NV, Zhu YS. Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. IEEE Trans Biomed Eng. 1991 Aug;38(8):785-794.

[5] Moody GB, Mark RG, Zoccola A, Mantero S. Derivation of respiratory signals from multi-lead ECGs. Computers in Cardiology 1985;12:113-116.

[6] Ding S, Zhu X, Chen W, Wei D. Derivation of Respiratory Signal from Single-Channel ECGs Based on Source Statistics. International Journal of Bioelectromagnetism 2004;6(2):43-49.

[7] Powell MJD. An efficient method for finding the minimum of a function of several variables without calculating derivatives. The Computer Journal 1964;7(2):155-162.

Address for correspondence:

Yanen Li
Department of Computer Science
University of Illinois, Urbana, IL 61801
Email: yanenli2@illinois.edu