Comparison of "black box" and "gray box" methods for lost data reconstruction in multichannel signals

S. Daukantas[1]*, M. Lukoševičius[2], V. Marozas[1], A. Lukoševičius[1]

[1]*Biomedical Engineering Institute, Kaunas University of technology, Lithuania*
[2]*School of Engineering and Science, Jacobs University Bremen, Germany*
**E-mail: saudauk@ktu.lt*

Introduction. Multichannel biomedical data is frequently used in research and clinical practice: in sleep studies, surgery, rehabilitation, sports medicine. The probability of a transient corruption or loss of one of the channels in a multichannel record is increased. Missing or corrupted signals can occur among others due to a human or machine error, a sensor malfunction, moving artifacts, or an external noise [3]. This problem of lost data is also common in real time wireless data transfer because of lost data packets.

The problem of lost data in multichannel biomedical data streams was addressed in a recent challenge organized by PhysioNet/Computing in Cardiology 2010: Mind the Gap [1].

In this work, we propose and compare two methods for reconstruction of a lost data channel in multichannel biomedical record.

Data. The set A of multichannel signals from the challenge [1] was used to compare the methods. In each ten-minute record, the final 30 s of one random signal was "lost" (deleted) (Fig. 1). The lost (target) signal is known, and provided with the data set A. The signal types for reconstruction are: 44 electrocardiograms (ECG), 15 fingertip plethysmograms (PLETH), 9 arterial blood pressure (ABP), 21 respiration (RESP) and 11 central venous pressure (CVP) signals.

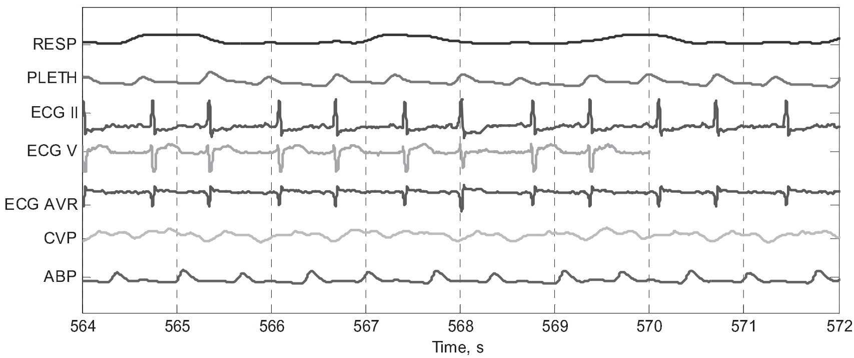

Fig. 1. Illustration of the multichannel record with 30 s lost data in the ECG V channel

Methods. Two methods were proposed and compared for signal reconstruction in this study.

The first method, called "gray box", is based on prior knowledge of physiological signals. It uses cyclic analysis of biomedical signals based on peak detection. The proposed "gray box" algorithm is shown in Figure 2.

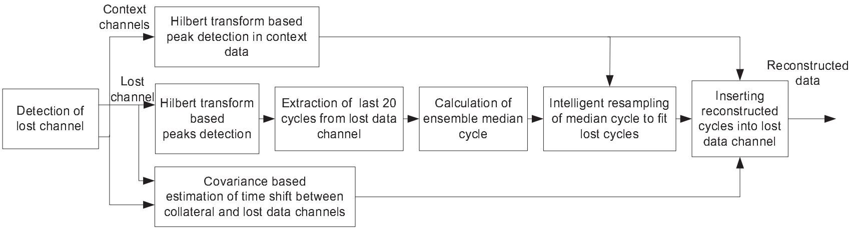

Fig. 2. Signal processing flow diagram of the "gray box" algorithm

The Hilbert transform and a cross-covariance function are used to estimate the peaks in the channels and phase differences among the channels. The ensemble of 10 - 20 cycles from the history of the lost data channel is used to calculate the median cycle. Intelligent resampling helps to adjust the length of the median cycle to fit the time slots defined by the peak indexes in the context data channels. The adjusted in lengths and time-shifted median cycles are combined to reconstruct the lost channel.

The second method, called "black box", uses a recurrent neural network of type Echo State Network (ESN) [4] and can be considered as a more general machine learning approach to reconstructing the lost data. The ESN is trained to reconstruct the lost channel from the context channels, using them as the input and the history of the lost channel data as the teacher signal (Fig. 3). The trained ESN is then used to generate the missing data from the last 30 s of the context channels.

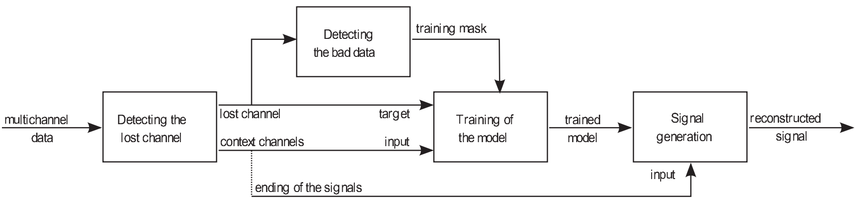

Fig. 3. Signal processing flow diagram of the "black box" algorithm

Scoring of methods. Two types of scores were used to compare the methods. The first score estimates the ability of methods to reconstruct the signal level:

$$Q_1 = \max\left(1 - \sum_{i=0}^{n} V_{res}\left(t_0 + i\Delta t\right)^2 \Big/ E_{ref}, 0\right). \tag{1}$$

where $V_{res}(t) = V_{rec}(t) - V_{ref}(t)$, the target signal is $V_{ref}(t)$ and the reconstructed signal is $V_{rec}(t)$. E_{ref} is calculated by

$$E_{ref} = \sum_{i=0}^{n} V_{ref}\left(t_0 + i\Delta t\right)^2 - \frac{1}{n}\left(\sum_{i=0}^{n} V_{ref}\left(t_0 + i\Delta t\right)\right)^2. \quad (2)$$

If $\sum V_{res}^2 = 0$, then the result is perfect, and $Q_1 = 1$ even if E_{ref} is also 0.

The second score *Q2* of a reconstruction is defined as the correlation coefficient of V_{ref} and V_{rec}, or 0, whichever is larger:

$$Q_2 = \max\left(corr(V_{ref}, V_{rec}), 0\right). \quad (3)$$

The use of the correlation coefficient provides a reliable estimation of the timing of major fluctuations in the signal (such as QRS complexes in an ECG signal), even if absolute signal levels are not recovered [2]. Both scores, *Q1* and *Q2*, have a range from zero to one.

Results. Examples of target and reconstructed signals using both methods are shown in Figure 4:

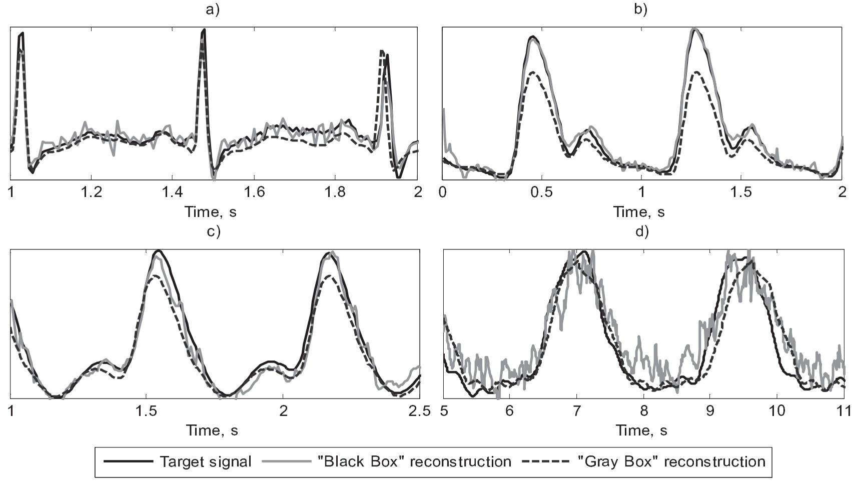

Fig. 4. Examples of the target and the reconstructed signals: a) ECG , b) ABP, c) PLETH, d) Respiration

It can be observed that the signals reconstructed by the ESN tend to be closer around the target but noisier than the "gray box" ones. Table 1 presents the results comparing the two methods.

Table 1. Signal reconstruction scores (mean ± std)

Target	"Gray box"		"Black box"		Attempted # of signals
	Q1	Q2	Q1	Q2	
ECG	0,64 ± 0,38	0,80 ± 0,26	0,85 ± 0,29	0,90 ± 0,24	44
ABP	0,49 ± 0,39	0,70 ± 0,32	0,77 ± 0,22	0,92 ± 0,08	9
CVP	0,33 ± 0,40	0,56 ± 0,41	0,49 ± 0,45	0,79 ± 0,20	11
PLETH	0,43 ± 0,37	0,65 ± 0,31	0,50 ± 0,30	0,69 ± 0,30	15
RESP	0,13 ± 0,30	0,28 ± 0,36	0,32 ± 0,29	0,60 ± 0,21	21
All	0,40 ± 0,37	0,60 ± 0,33	0,59 ± 0,31	0,78 ± 0,21	100

Discussion and Conclusions. As it is shown in Table 1, the Q2 reconstruction score is always higher than Q1. This is because the timing information is available from the context channels for the both methods, as opposed to the absolute magnitudes of the signal that are measured by the Q1 score.

Both methods have their pros and cons. The "gray box" method extracts a relatively few features from the data by using the signal-type-dependent knowledge. This makes it very robust (tolerating lots of missing/corrupted data), but the reconstruction relying on some very strong assumptions gives suboptimal scores. The "black box" model is "agnostic" towards the data (it doesn't "care" what it stands for) but uses every bit of it for learning. This more effective use of data yields better scores in all the categories here, but also makes it more sensitive to corrupted data. To mitigate this, the "black box" model also used a little bit of prior knowledge in a simple heuristic to detect the corrupted parts of the target signal and exclude them from learning, which gave a good improvement. This demonstrates that an ideal method should make an effective use of both the data and the prior specialist knowledge to achieve the best results.

The proposed methods for the lost data reconstruction have relatively low computing time, typically of several seconds, and can be implemented in real-time systems with some modifications.

References

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In this work, we propose and compare two methods for reconstructing a lost data channel in a multichannel biomedical record. The first method called "gray box" is based on prior knowledge of physiological signals. The second, "black box", method uses an echo state network (ESN) for signal reconstruction. The comparison results in terms of reconstructed signal level and periodicity show that the ESN-based method yields better scores for the same data set but also is more sensitive to corrupted data. Better reconstruction results could be achieved by using a combination of both methods.