Evaluation of Ensemble Averaging Methods in 3D Ballistocardiography

L. Lejeune, E. G. Caiani, G. K. Prisk, P-F. Migeotte

***Abstract*— Ballistocardiography (BCG) is a non-invasive technique which measures the acceleration of a body induced by cardiovascular activity, namely the force exerted by the beating heart. Measuring a BCG in a gravity-free environment provides ideal conditions where the subject is completely decoupled from its environment. Furthermore, because gravity constrains the motion in two dimensions, the non-negligible accelerations taking place in the third dimension are lost. In every experimental situation, the measured BCG signal contains artifacts pertaining to different causes. One of them is the undesirable involuntary movements of the subject. Ensemble averaging (EA) tackles the issue of constructing a typical one cardiac cycle BCG signal which best represents a longer recording. The present work compares state-of-the-art EA methods and proposes two novel techniques, one taking into account the ECG sub-intervals and the other one based on Dynamic Time Warping. The effects of lung volume are also assessed.**

I. Introduction

Ballistocardiography (BCG) is a non-invasive technique that measures the acceleration of a body induced by cardiovascular activity, namely the force exerted by the beating heart. Measuring a BCG in a gravity-free environment provides ideal conditions where the subject is completely decoupled from his environment. Furthermore, gravity constrains the motion in two dimensions and thus cancels the non-negligible accelerations taking place in the third dimension. In every experimental situation, the measured BCG signal contains artifacts pertaining to different causes. One of them is the undesirable involuntary movements of the subject. To minimize these artifacts, signal processing techniques can be applied. Ensemble averaging (EA) tackles the issue of generating a BCG signal of about one cardiac cycle which best represents the general shape of a set of beats. Alongside the BCG, an ECG is recorded. Previous studies relied solely on the R peaks to identify cardiac cycles and overlooked the intra-cycle variabilities. The Spacelab D2 flight in 1993 allowed the measurement of 3D-BCG, ECG, as well as the respiratory movements of the ribcage on a free-floating subject breathing normally. Because the lung volume has important consequences on the mechanical properties of the body [1], and thus affects the BCG, it is important to investigate breathing effects in the frame of EA by isolating heart-beats happening at Function Residual Capacity (FRC) and FRC + Tidal Volume (TV). Accordingly, the aim of this work was to compare four different methods of EA applied to 3D-BCG signals acquired during the Spacelab D2 flight. The first and simplest approach, the Constant Interval method, selects an interval of fixed length. The second one, RR scaling performs a homogeneous resampling of signals between two R peaks. The third one, further splits the signals with respect to the P and T waves (RTPR scaling). Finally, the Dynamic-Time-Warping-based method does a non-homogeneous and non-linear resampling.

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II. Methods

Both ECG and BCG signals were acquired with 1500Hz sampling rate. Prior to EA computation, the ECG signal is processed to extract several features. The R peak is detected by template matching. The T and P waves are detected in the same way and their respective maxima are extracted to represent the T and P "points". The implemented EA methods are now introduced.

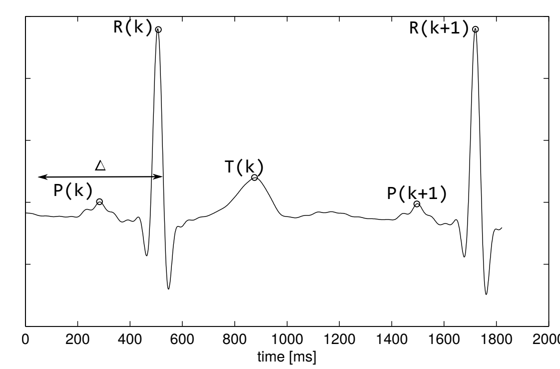

Fig. 1. Schematization of the segmentation of ECG intervals.

A. RR scaling method

Given the average RR interval in the acquisition, the RR scaling is applied for each cardiac cycle by considering two consecutive R peaks and the respective three components of the BCG signals. They are resampled at a fixed number of samples chosen as the average RR

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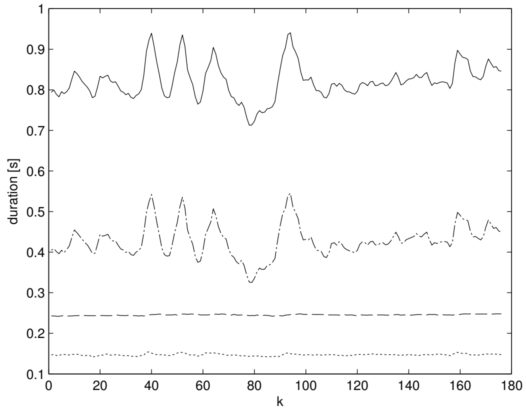

Fig. 2. ECG sub-intervals. Full line: RR, dashed: RT, dot-dash: TP, dotted: PR.

interval. The signals are then averaged to give the RR-scaled ensemble average. The segmentation of BCG beats spanning a full cardiac cycle allows one to reconstruct a closed velocity and displacement curve which brings insights on the geometry of the arterial tree[2].

B. RTPR scaling method

This method is based on the same principle as the previous RR scaling method, except that the RR interval is split into additional sub-intervals, namely RT, TP and PR. As expected [3], the RR interval variability is mostly due to the TP interval, and the RT and PR intervals remain relatively constant throughout the recording, as shown on figure 2. Thus, it is important to resample the three sub-intervals individually.

C. Constant interval (CI) method

A fixed interval is selected which takes into account the cardiac activity preceding the atrial depolarization. As shown in figure 1, the beginning of the $n-th$ interval starts before the P wave, at time $k_{n,start} = R_n - \Delta$ where R_n is the time instant of the R peak and Δ is two times the average PR interval duration. The end of the considered cardiac cycle is assumed as $k_{n,end} = R_n + E[RR_n]$ where RR_n is the RR interval duration.

D. Dynamic Barycenter Averaging (DBA) method

Dynamic time warping (DTW) allows performing a non-homogeneous and non-linear resampling of signals based on the minimization of a local cost. This approach was already used for the averaging of other cardiac signals[4], and the adopted implementation was described in [5]. The general idea behind DTW and the chosen averaging scheme are here summarized.

1) Averaging two waveforms: First, let $S_m(i)$ and $S_n(j)$, two sequences of duration I and J. The goal is to find the time warping function $c = c(k) = (i(k), j(k)), 1 \leq k \leq K$, which represents a correspondence between samples of S_m and S_n, such that a cost criteria is minimized. The TW function c is constrained to be monotonic and continuous. Also, slope constraints are added following the Itakura parallelogram method . This translates into the transition from $c(k-1)$ to $c(k)$ being of three types:

- Along a horizontal path, modelling a stretching of S_m and a shrinking of S_n.
- Along a diagonal path, preserving the original local shapes of the sequences.
- Along a diagonal of slope 2, stretching S_m twice as much as S_n.

Furthermore, the TW function observes the boundary conditions: $c(1,1) = 1$ and $c(K) = (I, J)$.

For each couple (i, j) observing those constraints, a local cost (or dissimilarity) is associated:

$$d(i,j) = |S_m(i) - S_n(j)| + |\dot{S}_m(i) - \dot{S}_n(j)|$$

The TW function $c(k)$ is then taken as the path that minimizes the cumulative dissimilarity recursive function given by:

$$\begin{aligned} D(i,j) = min(D(i,j-1) + d(i,j), D(i-1,j-1) \\ + 2d(i,j), D(i-1,j) + d(i,j)) \quad (1) \end{aligned}$$

2) Averaging multiple waveforms: The DBA method is heuristic, it starts from an initial guess A_0 and computes for each sequence S_m a TW function. The averaged waveform A_1 is then built by associating to $A_1(i)$ the average of the corresponding samples of the sequences. For the next iteration, A_1 is taken as initial guess and the procedure is repeated.

E. Comparison criteria

1) Average standard deviation: To quantify how well a given ensemble averaging method fits a set of BCG sequences, the average standard deviation (ADS) of the error was considered as a figure of merit. Let A_x, A_y, A_z three axes ensemble averages of a given method A calculated from a set of M sequences named $S_{m,x}$, $S_{m,y}$ and $S_{m,z}$. Both the EA and the individual sequences are of length N. The local error of method A with respect to the m-th sequence is given by:

$$e_{m,A}(n) = \left\| \begin{array}{c} A_x(n) - S_{m,x}(n) \\ A_y(n) - S_{m,y}(n) \\ A_z(n) - S_{m,z}(n) \end{array} \right\|$$

where $1 \leq n \leq N$ and $1 \leq m \leq M$.
The local standard deviation is obtained by:

$$\sigma_A(n) = \sqrt{\frac{1}{M} \sum_{m=1}^{M} (e_{m,A}(n) - \mu_A(n))^2}$$

with $\mu_A(n) = \frac{1}{M} \sum_{m=1}^{M} e_{m,A}(n)$
Finally, the average standard deviation is given by:

$$\bar{\sigma}_A = E[\sigma_A(n)]$$

TABLE I
AVERAGE STD OF ERROR $[10^{-}6m \cdot s^{-2}]$

Method	All beats	FRC	FRC+TV
RR	7.4	6.9	6.9
RTPR	6.7	6.4	6
CI	6.3	6.1	6.1
DBA	9.4	9.1	8.1

2) Maximum norm of acceleration: The maximum norm of the acceleration gives insight into the efficiency of cardiac contraction [2]. The terminology used in the results section is now introduced. Let $a_{max,m}$ be the maximum norm of the acceleration vector of the $m-th$ heart-beat. The mean and standard deviation of the $a_{max,m}$ are respectively written as $\bar{a}_{max}$ and $std(a_{max})$.

III. RESULTS

The analyzed data set from the D2 Spacelab experiment has a total of 128 heart beats, among which 32 are at FRC+TV and 32 at FRC. The 128 beats (referred to as the "All beats" case) are taken without any discrimination and are successive. The heart beats happening at FRC and FRC+TV have been selected manually using the rib-cage respiration sensor signal. The DBA method is initialized using the RR-scaled EA. The number of iteration was empirically set at 3: Additional iterations provided little changes.

A. Average standard deviation behaviour

Table I shows the ASD of the implemented methods. The RTPR method provides in all three cases (All beats, FRC and FRC+TV) an improvement over the RR method, respectively a drop of 8.5%, 13% and 7.3% in FRC, FRC+TV and all-beats case. Similarly, the CI method lowers the error by 7.7%, 8.3% and 4.7% with respect to the RTPR method. DBA performs systematically worse than all three simpler methods under this criterion.

As visible on the ECGs in figures 3, 4 and 5, the CI method sometimes averages not corresponding parts of the signal after the R peak of the considered cardiac cycle. As a consequence, its EA has a higher error near the end of the interval compared with the scaled methods.

B. Comparison of a_{max}

The methods are now compared with respect to the maximal acceleration. Figure 6 shows how their estimation of $\bar{a}_{max}$ compares with respect to the experimental data in the all-beats, FRC and FRC+TV cases. The RR scaling method underestimates that value in all three cases. The RTPR and CI methods give similar results. In the FRC+TV case, RR, RTPR and CI methods estimate a value below the confidence interval. DBA performs slightly better.

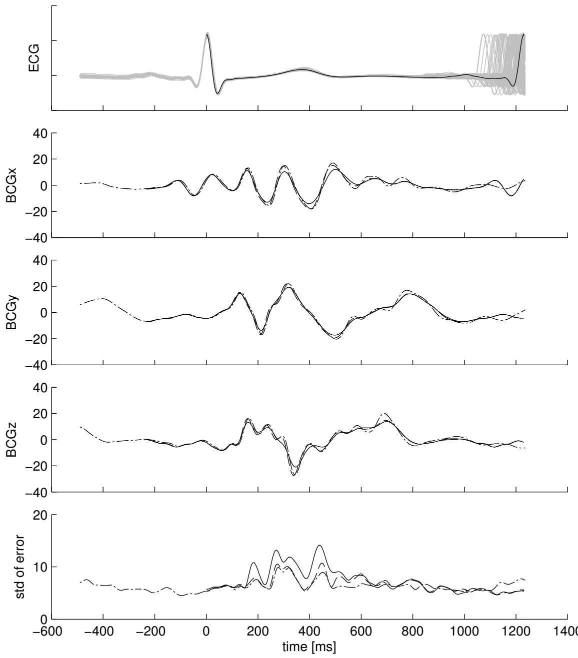

Fig. 3. Ensemble average curves for all beats. From top to bottom: ECG, three axes BCG (full line: RR method, dashed line: RTPR method, dot-dash line: CI method) and standard deviation of error. BCG accelerations and standard deviation of error are given in $10^{-3}ms^{-2}$.

C. Qualitative observations of DBA

Figure 7 shows how the CI and DBA method behave in the three breathing cases. Interestingly, when given all beats, the DBA method manages to recover features that are only present at FRC, while preserving the overall shape rendered by the CI method. This is most clearly apparent in the diastolic phase at $t \in [500; 900]ms$.

IV. CONCLUSION

This work has provided a general overview of Ensemble Averaging methods applicable in the frame of 3D ballistocardiography. The comparison between the RR and the RTPR methods showed that the introduction of the cardiac-cycle sub-intervals in the averaging computation is indeed relevant. The CI method offers the lowest overall estimation error, when computed as ASD, in the tested methods. However, it tends to add perturbations near the end of the EA curve due to the shorter heart beats. Also, it is conceptually incompatible with the reconstruction of the displacement because of its non-periodical nature. The Dynamic Barycenter Averaging method offers interesting capabilities not found in other methods. It allows recovering FRC and FRC+TV features in the diastolic phase that are attenuated or even cancelled by other simpler methods when all beats are considered. This could prove valuable in experimental scenarios where the respiration signal is not available. Its overall estimation error might be improved by tuning both its initial condition and path constraints. Concern-

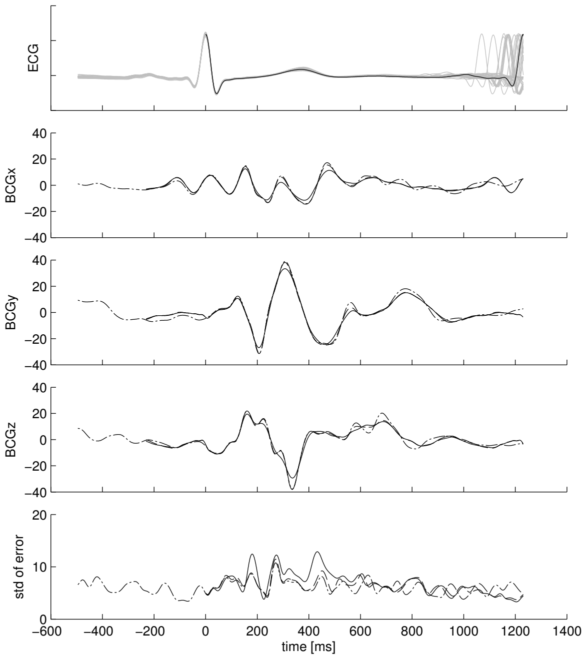

Fig. 4. Ensemble average curves at FRC. From top to bottom: ECG, three axes BCG (full line: RR method, dashed line: RTPR method, dot-dash line: CI method) and standard deviation of error. BCG values are given in $10^{-3}ms^{-2}$.

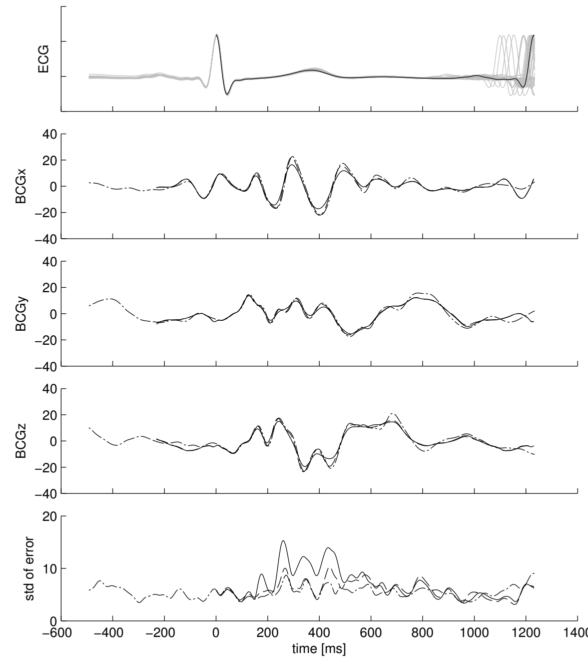

Fig. 5. Ensemble average curves at FRC+TV. From top to bottom: ECG, three axes BCG (full line: RR method, dashed line: RTPR method, dot-dash line: CI method) and standard deviation of error. BCG values are given in $10^{-3}ms^{-2}$.

ing the maximum acceleration, the RR scaling method has shown to be underestimating the experimental data. RTPR and CI provide near identical results in all three breathing cases, whereas DBA provides a noticeable improvement in the all-beats case.

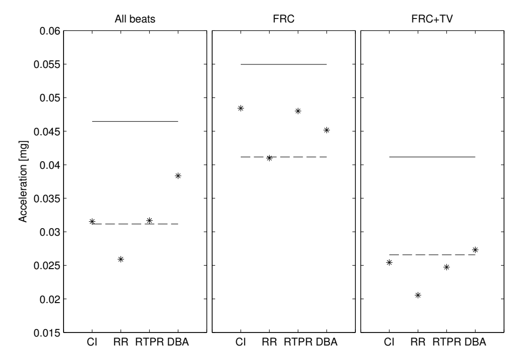

Fig. 6. Comparison of the EA-estimated a_{max} values. The full line is $\bar{a}_{max}$, the dashed line is $\bar{a}_{max} - std(a_{max})$.

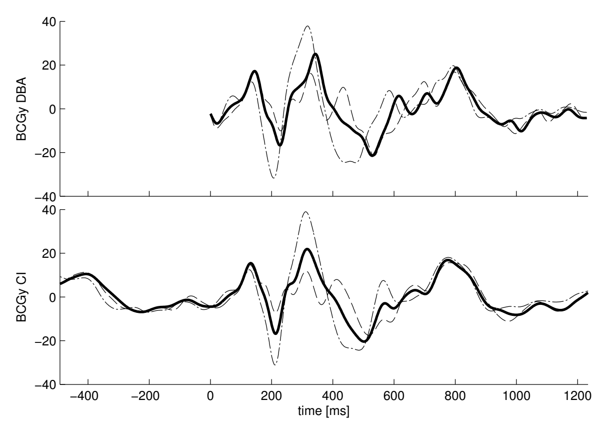

Fig. 7. DBA (top) vs CI (bottom). Bold line: all beats average, dot-dash line: FRC average, dashed line: FRC+TV average.

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